Sourcing and Capacity Investment Decisions in Supply Chain Risk Management

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Dedication

To my parents

Abstract

Risks are prevalent in supply chains. While managers are familiar with common risks such as supply disruption and demand uncertainty, new risks are constantly emerging. These emerging risks may differ from the existing ones in important ways that alter the decision setting, requiring managers to adopt new risk management strategies. Using old strategies to respond to these emerging risks may be ineffective or even counterproductive. Through three studies, this dissertation examines how sourcing and capacity investment decisions are influenced by two categories of emerging risks—supplier-induced risks and regulatory risks. Studies 1 and 2 use analytical models and behavioral experiments to compare how buyers' optimal and actual sourcing strategies differ under supplier-induced responsibility violation risks and traditional supply disruption risks. We document significant and robust differences in buyers' ordering behaviors across the two risk types and further disentangle the effects of risk structure and context characteristics that drive the differences. Our additional analysis on the performance implications of different sourcing strategies shows the promise of sole-sourcing from the risk-free supplier and identifies cognitive and affective behavioral factors associated with adopting this strategy. Study 3 uses analytical models and a numerical study to examine a vaccine manufacturer's optimal capacity investment strategy across domestic and overseas markets when faced with a potential risk emanating from regulations that restrict vaccine exports from the domestic market. We characterize how a regulatory mandate may shift the manufacturer's overall capacity commitment strategy (produce in one location vs. both) as well as the associated capacity levels in each location. We further assess the impact of these changes on service level and public health outcomes at both locations as well as globally. A general theme of this dissertation is to investigate when diversification, a common strategy used to handle risks, is warranted in these problem domains from normative and behavioral perspectives.

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Chapter 1

Introduction

1.1 Overview

Globalization enhances connectivity between nations and has the potential to deliver substantial benefits to firms. Such opportunities allow firms to access a more diversified set of supply sources and to leverage cost or technology advantages elsewhere to enhance their value-creation processes. They also open doors to a broader set of demand markets, generating additional revenue streams. However, these potential benefits also come with new risks and challenges that have important implications for supply chain management. Without a good understanding of how these risks impact their supply chains and what tools are available to counteract them, managers might find it challenging to navigate these emerging challenges. This dissertation focuses on two sources of such emerging risks—suppliers and government regulations—and seeks to provide insights to help managers better handle risks associated with sourcing (Studies 1 and 2) and capacity investment decisions (Study 3).

1.2 Study 1: Sourcing Under Supply Disruption and Responsibility Violation Risks: A Behavioral Investigation

Responsibility-related issues at suppliers' sites are attracting increased attention in the media and increased scrutiny from NGOs and consumers, making sourcing decisions more complex. Study 1 examines this type of emerging risk along with traditional supplier-induced risks. More specifically, we present a comparative framework to contrast buyers' sourcing decisions in light of two types of supplier-induced risks that shape the supply-demand balance: responsibility violation risk that could influence a firm's demand (e.g., Guo et al. 2016) and the relatively well-studied supply disruption risk that influences the quantity of products available for sale (e.g., Gurnani et al. 2014). We analyze settings involving one buyer and two suppliers in which sourcing from one supplier is risk-free, whereas sourcing from the other introduces either supply disruption or responsibility violation risk. Inspired by risk matrices frequently used in practice, we characterize risk by its likelihood (i.e., the probability of the disruption or violation) and impact (i.e., the fraction of supply or demand lost in the event of a supply disruption or responsibility violation), respectively. We address the following research questions: (1) How does buyer sourcing behavior vary when faced with the risk of supply disruption versus responsibility violation? (2) How do the likelihood and the impact of a disruption or violation influence buyers' decisions under the two risk types? (3) What implications does buyer sourcing behavior have on key performance measures?

We first utilize analytical models to set benchmarks for buyers' profit-maximizing strategies given different risk likelihood and impact levels. We then test how individuals actually behave in an incentive-compatible experiment, with participants recruited from Amazon Mechanical Turk (MTurk) acting as buyers in a sourcing task. The experiment utilizes a mixed design with risk type manipulated between-subjects (supply disruption risk vs. responsibility violation risk) and decision scenario manipulated within-subjects (3 levels of risk likelihood $\times$ 4 levels of risk impact). In total, 217 MTurk participants (53.0% male; $M_{age} = 39.5$) completed all of the required activities. Our analyses reveal the following insights:

(1) From a normative perspective, sole-sourcing is always the profit-maximizing strategy under the two risk types. Furthermore, under both risk types, an impact threshold separates the high and low impact conditions; within each condition, likelihood further determines the buyer's optimal sourcing strategies. The high-cost supplier only becomes an attractive choice when the impact is high. When the impact is low, the low-cost supplier is always optimal, and the order quantity may deviate from demand if the likelihood is sufficiently high. The direction of this deviation differs across the two risk types: the order quantity is set lower than demand under responsibility violation risk to ensure there is no leftover inventory if a responsibility violation occurs, while it is set higher than demand under supply disruption risk to ensure there is sufficient inventory to meet demand in case of a supply disruption.

(2) Buyers in the behavioral experiment tend to diversify their orders across the two suppliers, with more diversification under supply disruption risk relative to responsibility violation risk. In addition, buyers under responsibility violation risk are more likely to correctly sole-source from the high-cost supplier. But when the low-cost supplier is the optimal solution, there is no significant difference between the two risk types regarding buyers' tendency to correctly sole-source from that supplier.

(3) Despite the aforementioned differences with respect to diversification and correct sole-sourcing behaviors, we do observe important similarities in buyers' ordering behavior across the two risk types. Specifically, participants adjust their order allocations similarly across the two risk types when risk likelihood increases, even though more customized strategies would be beneficial.

(4) The behavioral tendencies mentioned previously result in a significant loss in expected profit, especially under responsibility violation risk.

Taken together, the findings highlight that buyers' ordering behavior deviates from the normative benchmarks and, more importantly, there are critical differences in buyers' ordering behavior across the two risk types in terms of diversification and preference of supplier to source from. Since the decision settings under the two risk types differ in multiple dimensions, identifying the primary source of the variation is challenging. In the following study, we provide a parsimonious approach to delineate the characteristics of the decision settings under the two risk types and disentangle the underlying driving forces.

1.3 Study 2: Supply Disruption vs. Responsibility Violation Risks: The Influence of Structure and Context

Building on the results of Study 1, in Study 2, we continue our inquiry into buyers' sourcing behavior under supply disruption and responsibility violation risks. Specifically, we have three goals for Study 2. First, we attempt to identify the underlying forces that drive differences in buyers' sourcing behaviors between the two risk types identified in Study 1. Based on our risk taxonomy in Study 1, we introduce three additional risk types to disentangle the effects of *structure* (i.e., whether a risk influences the supply or demand side of the supply chain and whether the influence is focal to the impacted supplier or crosses over to the entire supply base) and *context* (i.e., whether the risky event is a process disruption or business practice violation). Second, we aim to replicate the results of Study 1 regarding buyers' different ordering behaviors across the two risk types by using a different subject pool with management experience. Finally, we explore how buyers' sourcing strategies influence their profits and what behavioral factors are associated with their specific strategy choices. We address the following research questions in Study 2: (1) Are the main insights revealed in Study 1 robust to managerial experience and the assistance of decision support? (2) What structure and context characteristics drive buyers' ordering behavior? (3) How do buyers' sourcing strategies influence their profit performance?

We recruited participants with management experience from the Prolific academic platform to perform the same sourcing task as in Study 1. We consider five different treatments in Study 2: in addition to the supply disruption and responsibility violation risks considered in Study 1, we introduce three new treatments that systematically vary the structure and context characteristics. In total, 531 participants (57.1% male; M_{age} = 43.4) completed all of the required activities. Our results show that:

(1) Buyers' ordering behaviors under supply disruption and responsibility violation risks differ significantly in a way that aligns with the patterns we observe in Study 1, which confirms the robustness of the results.

(2) Structure characteristics, especially whether the influence of the risk crosses over to the entire supply base, play a dominant role in influencing buyers' ordering patterns. In contrast, the context characteristic appears to have a limited influence as it matters only for settings with certain structure characteristics.

(3) Diversification leads to a substantial erosion of profits, but sole-sourcing from the high-cost supplier appears to be an attractive strategy. This is because it helps avoid the suboptimal behavior of diversification and profit losses associated with erroneous order quantity adjustments.

(4) Our analysis of the connection between individual differences and sourcing strategies reveals that cognitive and affective factors are at play. Specifically, the perception that the overall risk exposure linearly increases with sourcing quantity from the low-cost supplier significantly increases the likelihood of diversification when the influence of the risk crosses over to the entire supply base. In contrast, buyers who perceive the low-cost supplier to have more control and responsibility for the risky event are less likely to diversify and more likely to sole-source from the high-cost supplier.

These insights suggest that buying firms have opportunities to nudge managers to make better decisions by focusing on these two behavioral factors. By doing so, they are more likely to adopt sourcing strategies that can improve their profit performance. In addition, if such risks involve business practice violations, these strategies also have the potential to lead to better societal outcomes, creating a win-win scenario.

1.4 Study 3: Capacity Investment in Global Vaccine Supply Chains under Regulatory Risks

In Study 3, we shift our attention from supplier-induced risks to regulatory risks and examine how they influence capacity investment decisions in global vaccine supply chains. The COVID-19 pandemic illustrates how global crises can create considerable pressure on healthcare supply chains. Given the vital role of vaccines in efforts to combat the pandemic, a number of governments have enacted vaccine export controls in various forms (e.g., Vela and Heath 2021, Williams and Stacey 2021), despite warnings from a variety of relevant communities on the danger of "vaccine nationalism" (e.g., Weintraub et al. 2020, Kupferschmidt 2020). Such government interventions to limit exports present unique challenges to vaccine manufacturers with respect to managing their international production and distribution networks. In this study, we refer to the country or market from which export is banned as the 'domestic' market. We refer to other locations where there is demand for the production in question as the 'overseas' market. This study aims to examine the impact of such regulatory mandates on a vaccine manufacturer's capacity investment decisions and the resultant effects on service level and public health outcome. Specifically, we investigate the following research questions in Study 3. (1) When faced with a regulatory mandate, how does a vaccine manufacturer change its capacity commitment strategy (i.e., pool all production in the domestic market vs. produce in both markets) and corresponding capacity levels? (2) How do these decisions change based on the type of regulatory mandate imposed? (3) What implications do these decisions have on key performance measures related to vaccine availability and public health outcome?

We study the impact of two types of regulatory mandates: a random ban, where there is a probability that the government could ban export to the overseas country outright, and priority requirement, where the firm must ensure it meets all domestic demand before being allowed to export. Our analytical models and numerical study reveal the optimal capacity investment strategy for a vaccine manufacturer and the associated policy implications for the domestic government. Specifically, our results show that:

(1) The implementation of a regulatory mandate might induce the manufacturer to change its capacity commitment strategy from pooling (i.e., investing in capacity only in the domestic market) to diversifying (i.e., investing in the domestic and overseas markets). The manufacturer always diversifies if it is most profitable to fulfill overseas demand with overseas capacity.

(2) In general, a random ban is more likely to induce a change in the manufacturer's strategy than the priority requirement. The domestic country's population advantage over the overseas country increases the likelihood that the manufacturer needs to change its strategy under the priority requirement but reduces that likelihood

under a random ban.

(3) A random ban always results in a decrease in the manufacturer's domestic capacity level, whereas a priority requirement could lead to an increase or decrease in its domestic capacity level.

(4) A reduction in domestic capacity level does not necessarily result in a lower domestic service level since the imposed regulatory mandates effectively reserve a larger portion of the available vaccine capacity for the domestic market. However, in circumstances where mandates lead to a severe reduction in the domestic capacity, both domestic service level and public health outcome suffer. Hence, governments should be extremely wary and mindful of the unintended consequences of imposing such mandates.

The rest of this dissertation is organized as follows: Chapter 2 surveys the relevant operations and supply chain literature related to managing risks in sourcing and capacity decisions, and highlights how the studies in this dissertation differ from and complement prior research. The details of this dissertation's three studies are presented in chapters 3, 4 and 5. This dissertation concludes with chapter 6, which summarizes the key insights related to sourcing and capacity investment decisions when faced with supplier-induced risks and regulatory risks, respectively.

Chapter 2

Literature Review

2.1 Sourcing Decisions and Supplier-induced Risks

Supply and demand uncertainty are common in supply chains, and mismatches between the two can result in substantial economic loss (Snyder and Shen 2007). Prior research on supply uncertainty has focused on identifying the types and sources of supply disruptions and analyzing methods of managing specific risks (Vakharia and Yenipazarli 2009). Gurnani et al. (2012) and Kouvelis et al. (2011) discuss different issues related to managing supply disruptions, including inventory management and contracting, from analytical and empirical perspectives and offer risk management strategies that utilize both operational and financial levers. Snyder et al. (2016) provide a recent comprehensive survey of analytical studies on supply chain disruptions. These studies demonstrate that the choice of suppliers is a vital aspect of coping with and recovering from supply chain disruptions. Prior research also utilizes behavioral methods to investigate sourcing issues in managing supply disruptions (e.g., Gurnani et al. 2014). In a systematic review of the supplier selection literature, Wetzstein et al. (2016) further remark that "Behavioral issues in SS [supplier selection] will receive further academic attention from both an analytical and empirical perspective." (p. 320)

Although they are not as well-studied as supply disruptions, social and environmental responsibility issues are receiving increased scrutiny from customers and NGOs, leading to greater scholarly attention, particularly from the operations management research community (Lee and Tang 2018). For example, prior analytical studies have examined child labor (e.g., Cho et al. 2019) and hazard materials (e.g., Kraft et al. 2013) in supply chains and have proposed solutions, including auditing and inspections (e.g., Plambeck and Taylor 2016, Dawande and Qi 2020), supplier improvement investments (e.g., Kraft et al. 2020), and other contracting methods (e.g., Chen and Lee 2017). As previously discussed, suppliers' potential lack of compliance with social and environmental standards imposes risk on the buyer through its impact on customer perception and ultimately, demand. The choice of the upstream supplier may expose the buyer to potential customer boycott and as a result, risk mitigation strategies aimed at tackling supply disruptions may prove ineffective in managing the demand-side influence (e.g., Guo et al. 2016, Huang et al. 2017). Our study contributes to an emerging stream of literature that investigates sourcing decisions under responsibility violation risk through a behavioral lens (e.g., Mahmoudzadeh and Siemsen 2019). More importantly, our research provides a framework to analyze sourcing decisions under risks of supply disruption and responsibility violation and unify the two streams of literature, allowing us to compare the influence of the two risk types on buyers' sourcing decisions.

Five behavioral studies on sourcing decisions are particularly relevant to our study. Csermely and Minner (2015) analyze tradeoffs between speed and cost in a dual-sourcing setting comprised of a fast but expensive supplier and a slow but cheaper supplier. They find that having the fast option available is beneficial even though participants tend to overuse this option. Our study differs from this work in that we evaluate the impact of risk differences, rather than lead times, on supplier selection. Goldschmidt et al. (2020) examine how the presence of high-impact, low-probability disruptions influences buyers' choice of the supply base from a group of homogeneous suppliers. They find that people under-diversify on average and tend to only temporarily increase the number of suppliers immediately after the occurrence of a disruption. We examine a different scenario in which the buyer faces heterogeneous suppliers. Furthermore, our model is not constrained by the requirement to split orders equally among all chosen suppliers, and there is no fixed cost for maintaining relationships with each supplier.

Gurnani et al. (2014) examine sourcing decisions when a buyer faces a reliable but expensive supplier and an unreliable but cheaper supplier, in a setting involving compounded risks of both supply disruption and yield uncertainty. They find that participants in a controlled laboratory environment tend to diversify, although it is theoretically optimal to sole-source. A model of bounded rationality is proposed to explain this diversification bias. Our research framework builds on this study by considering two different risk types that may influence a firm's supply and demand, respectively. In addition, our analysis of influencing behavioral factors sheds light on potential contributors to diversification bias in sourcing decisions. Kalkanci (2017) focuses on risk mitigation strategies to combat supplier capacity uncertainty, comparing supplier diversification and improvement options. The experimental results show that buyers do not diversify as effectively as the optimal solution suggests (they order more evenly across the two suppliers) but rather choose improvement efforts that are more consistent with theory. Our research setting is different because we compare sourcing decisions under the risks of supply disruption and responsibility violation, while Kalkanci (2017) contrasts two different options to handle supplier capacity uncertainty.

Building on Guo et al. (2016), Mahmoudzadeh and Siemsen (2019) develop a behavioral model to examine buyers' dual-sourcing behavior induced by customer segmentation in a responsible sourcing context. They evaluate the effectiveness of different tactics to influence customer reactions to promote responsible sourcing. In contrast, our study focuses on buyers' sourcing decisions when faced with two different types of risk and documents the existence of diversification bias even when the market is not segmented. Finally, while Mahmoudzadeh and Siemsen (2019) focus on the cognitive aspect of decision-making, our work considers both cognitive and affective aspects (e.g., Weber and Johnson 2009, Loewenstein et al. 2001).

2.2 Capacity Investment Decisions under Risks

Capacity planning problems have always been a key part of firms' operations (Van Mieghem 2003, Song et al. 2020). As more firms expand their business presence to new geographies, it becomes critical to carefully design their production network to coordinate across locations. Thanks to globalization and booming international trade, more firms have had the opportunity to enter other countries to build factories and sell to local markets. For multinational firms and their global supply chains, the capacity design issue is even more critical since it requires extra lead time for planning and execution. Facing a series of interesting phenomena and questions in this domain, operations management researchers have utilized different approaches to tackle these challenges, offering many practical insights to guide firms' global network capacity decisions.

One framework that has received particular attention is the newsvendor network (Van Mieghem and Rudi 2002). It has been widely used to study multi-location capacity and inventory problems, especially in global supply chains. For example, Lu and Van Mieghem (2009) adopt this framework to analyze the network design and reshoring decisions of an international firm that needs to set up a manufacturing network for a common component used in all products and local assembly lines that tailor to the specific needs of different countries. The key risk in setting capacity levels arises from demand uncertainty, but other factors, such as exchange rate fluctuations, are also considered (e.g., Dong et al. 2010). Our study introduces emerging regulatory risks to this stream of literature and highlights how this risk influences the manufacturer's capacity commitment strategy and subsequent fulfillment decisions.

Risks associated with governmental policies in global supply chains are not new in operations literature. Prior studies have examined a variety of issues concerning tax, tariff, and trade policies and their associated risks, and their influence on procurement (e.g., Wang et al. 2011), supply base (e.g., Chae et al. 2019), postponement strategy (e.g., Choi et al. 2012), and supply chain configuration (e.g., Hsu and Zhu 2011). However, this literature typically focuses on governments' economic incentives in international trade (e.g., Dong and Kouvelis 2020). A series of recent incidents reveal governments' other motives related to nationalism and national security. In addition, national governments have been increasingly likely to implement active interventions. As these interventions create new complications in supply chain management, as exemplified in the COVID-19 pandemic (Pournader et al. 2020), it is important to understand how this form of emerging political risk can potentially influence supply chain capacity design and supply chain resilience (Song et al. 2020). Current literature does not provide needed guidance for firms to react and manage these risks. This study intends to bridge this gap and offer insights that will not only benefit firms for their operations during emergencies but also guide their long-term planning in the post-COVID era, as more and more governments are revising their national supply chain strategies (e.g., Wilkie 2021, Weiss 2021). From the government's perspective, this study evaluates the efficacy of such regulatory mandates so that governments can understand what these mandates may entail and make informed decisions accordingly.

Our research also directly connects to vaccine supply chain literature, especially research on vaccine production (Duijzer et al. 2018). This component of the vaccine supply chain faces risks associated with supply and demand. On the supply side, due to the production technologies involved, supply reduction resulting from yield uncertainty is a common issue for certain vaccines, such as influenza (Deo and Corbett 2009). On the demand side, the quantity of vaccines needed is difficult to forecast due to complex contextual as well as individual factors (MacDonald 2015). For example, during the COVID-19 pandemic, in addition to the influence of the anti-vaccination movement and general vaccine hesitancy (Blume 2006, Johnson et al. 2020), the concern over rapid development and approval of COVID-19 vaccine candidates is cited by some people as an important reason for not wanting to be vaccinated (Tyson et al. 2020).

Our study differs from this broad stream of literature in two ways. First, we examine vaccine production issues during sudden outbreaks, which has not received enough attention in prior research (Duijzer et al. 2018). Second, we shed light on the influence of risks that arise from governments' regulatory interventions on vaccine supply chains. National governments' moves, which aim at improving domestic welfare, negatively affect the availability of vaccines to other countries, significantly influencing vaccine allocations (Duijzer et al. 2018) and enlarging disparity. To quantify the impact from different angles (Lemmens et al. 2016), we not only consider service level but also measure public health outcomes by taking into account the herd immunity effect (Fine et al. 2011).

Chapter 3

Study 1: Sourcing under Supply Disruption and Responsibility Violation Risks: A Behavioral Investigation

3.1 Introduction

Enhanced international connectivity enables companies to operate on a global scale, allowing access to diversified supply bases. While this development facilitates opportunities to lower sourcing costs, it also introduces new challenges as low-cost suppliers in remote locations may expose buying firms to new risks. Against this backdrop, supplier selection has become increasingly complex as sourcing managers must balance between different cost levels and risk types to ensure a steady supply-demand stream.

Previous research examining the influence of supplier-induced risks on sourcing decisions focuses primarily on *supply disruption risk*, which can lead to potential interruptions in the supply line (see, e.g., Snyder and Shen 2007, Snyder et al. 2016). This includes yield losses due to machine breakdowns or material shortages, or more significant supply disruptions due to plant closures or natural disasters. However, less research has examined how suppliers might expose a firm to *responsibility violation risk*, which has potential demand-side ramifications. For example, suppliers' failure to engage in responsible practices — such as exposing employees to unsafe working conditions, employing child labor, or using environmentally harmful materials in their products — can lead to customer boycotts and subsequent reductions in demand for buying firms (e.g., Barton et al. 2018). One company recently plagued by such responsibility violations is global food giant Nestlé, which faced allegations of forced labor and child labor issues in its supply chains, eventually leading to customer boycotts (Kelly 2016, Vasil 2016). As customer awareness of such incidents and NGOs' attention to corporate responsibility increase, the prospect of responsibility violations raises new challenges with respect to firms' sourcing decisions.

Responsibility violations, once reported, can attract serious negative publicity for brands and firms. Unlike news coverage for supply disruptions, which commonly focuses on specific incidents, press for responsibility-related issues may generalize to harsh judgment for firms' overall business conduct, resulting in broader consequences that spill over to other business units within the firm. Furthermore, as customers are willing to take actions to punish firms or brands they perceive as irresponsible or unaccountable, the potential loss in customer loyalty and market share can be more difficult to tackle. Facing a risk that results in losses on the supply side, firms may buffer from negative consequences through higher inventory levels or larger order quantities. However, once exposed to a risk that influences the demand side, firms have limited operational levers available to counteract strategically. The broader consequences and a lack of effective countermeasures to violation events highlight the structural differences between supply disruption and responsibility violation risks. These differences imply a higher financial stake of brand degradation under responsibility violation risk, which requires buyers facing this emerging type of risk to engage in a different cognitive processing mode when conceiving their sourcing strategies.

In addition to structural differences, the context of the events that each risk potentially triggers are also different. While potential supply disruptions and responsibility violations are both unpleasant, the latter context can be more negatively emotion-laden (Luce 1998). Due to the possibility of collaborating with unethical businesses and being portrayed as an irresponsible firm in the news, buyers may be reluctant to source from a risky supplier with low-cost. In addition, while supply disruptions might be perceived as exogenous to the control of suppliers (and the buying firm, by association), responsibility violations require suppliers' direct participation. Hence, buyers may regard sourcing from suppliers with limited business practice visibility as an endorsement of such questionable behaviors. As prior research has shown that people's moral judgments differ for harm resulting from omissions vs. commissions (e.g., Sparanca et al. 1991), intentional engagement with suppliers with potential business conduct issues might activate buyers' affective responses differently than purchasing from suppliers with potential business disruptions. Therefore, buyers facing responsibility violation risk in their supply chains are confronted with a decision-making context with stronger emotional valence.

In this study, we present a comparative framework to examine buyers' sourcing behavior when faced with different types of supplier-induced risks that may lead to supply-demand imbalance. We utilize the setting of a buyer who faces two suppliers: sourcing from one supplier costs more but involves no risk, while sourcing from the other costs less but may introduce either supply disruption risk or responsibility violation risk. In deciding how to allocate orders between the two suppliers, the buyer's cognitive processing and affective reactions may be activated in different ways, depending on the type of risk involved. Within this context, our study addresses the following research questions: (1) How does buyer sourcing behavior vary when faced with the risk of supply disruption versus responsibility violation? (2) How do the likelihood (i.e., the probability of the disruption or violation) and the impact (i.e., the fraction of supply or demand lost in the event of a supply disruption or responsibility violation) influence buyers' decisions under the two risk types? (3) What implications does buyer sourcing behavior have on key performance measures?

We address these questions by first analyzing the structure of buyers' profit-maximizing sourcing strategies using analytic models. We demonstrate that under both risk types, sole-sourcing is always optimal, and the specific optimal sourcing strategy (i.e., which supplier to source from and how much to order) varies based on likelihood and impact levels. Against these normative benchmarks, we then develop behavioral hypotheses and test them using an experiment with incentivized human participants to examine individuals' actual sourcing decisions across the two risk types. In our analysis, we examine (i) whether buyers diversify, and (ii) whether buyers' supplier preferences differ from the optimal solution.

Our experimental data show that buyers facing responsibility violation risk diversify less than those facing supply disruption risk. The former group is also more likely to correctly select the optimal supplier when the high-cost supplier is the optimal choice, but there is no difference between the two groups when the low-cost supplier is optimal. Despite these differences, buyers react to changes in likelihood levels in a similar way across the two risk types. Whenever the likelihood level increases, buyers divert more orders to the high-cost supplier. This behavior exhibits in high-impact scenarios, where it directionally aligns with optimal solutions, but also in low-impact scenarios, where buyers should only consider the low-cost supplier. Finally, our analysis on buyers' profit reveals that the negative influence of these ordering behaviors on profit can be quite significant, especially under responsibility violation risk. These findings underscore the critical need for managers to understand how the two risk dimensions uniquely influence a firm's overall exposure and highlight the importance of developing tailored strategies to manage and mitigate different types of supplier-induced risks.

The remainder of the chapter is organized as follows. In section 3.2, we present the comparative framework, which serves as the basis for our analytical models and behavioral hypotheses. In section 3.4, we describe our experimental design, followed by an analysis of the experimental results in section 3.5 and post-hoc analysis in section 3.6. We conclude in section 3.7 with a discussion of the implications of our study findings and directions for future research.

3.2 Comparative Framework and Normative Benchmarks

To inform our behavioral hypotheses, we first introduce a comparative framework that captures the sourcing tradeoff faced by a buyer (e.g., a sourcing manager within a retail firm) seeking to procure a product that will be sold at retail price p to a potential demand base of d units within a single selling season. The buyer chooses how much to order from two supplier candidates, knowing that any product available in excess of demand has no salvage value. The suppliers offer products of the same quality but differ in both wholesale price and potential risk. Sourcing from the high-cost supplier (denoted as H) involves no risk but incurs a higher per-unit cost c_H. Sourcing from the other supplier (denoted as L) incurs a lower cost c_L ($c_L < c_H < p$; $c_\Delta \equiv c_H - c_L$) but introduces the risk of either a supply disruption (SD) or a responsibility violation (RV). To capture the most essential characteristics of the two types of risk, we draw inspiration from risk matrices, which have been frequently used by companies and organizations in practice to manage a variety of uncertainties. Such matrices often depict risk through two dimensions—likelihood and impact—with each cell of the matrix indicating the appropriate strategy when faced with a certain likelihood and impact level. Inspired by these matrices, we also characterize risk in our research by its likelihood (i.e., the probability of a disruption or violation; denoted by δ_i, $i = SD, RV$) and its impact (i.e., the consequence of the disruption or violation; denoted by γ_i). In this setting, the buyer's sourcing decision is to choose how much to order from each supplier, denoted by Q_j, $j = L, H$, with $Q = Q_L + Q_H$.

3.2.1 Normative Benchmark for Supply Disruption Risk

First, consider the case where sourcing from the low-cost supplier introduces the possibility of a supply disruption. We denote the likelihood of the disruption by $\delta_{SD} \in (0, 1)$. The impact is captured by the parameter $\gamma_{SD} \in (0, 1]$, which represents the proportion of products that would not be delivered if a disruption occurs. Specifically, if supplier L experiences a disruption, the buyer will only receive and pay for a fraction of the ordered quantity, i.e., $(1 - \gamma_{SD})Q_L$. The buyer's expected profit in this scenario is as follows:

$$\begin{aligned}\pi_{SD}(Q_L, Q_H) =& (1 - \delta_{SD})p \min\{Q_L + Q_H, d\} + \delta_{SD} p \min\{(1 - \gamma_{SD})Q_L + Q_H, d\} \\ &- (1 - \gamma_{SD}\delta_{SD})Q_L c_L - Q_H c_H.\end{aligned} \tag{3.1}$$

Proposition 3.1 characterizes the buyer's profit-maximizing sourcing strategy under SD. All proofs are provided in the Appendix.

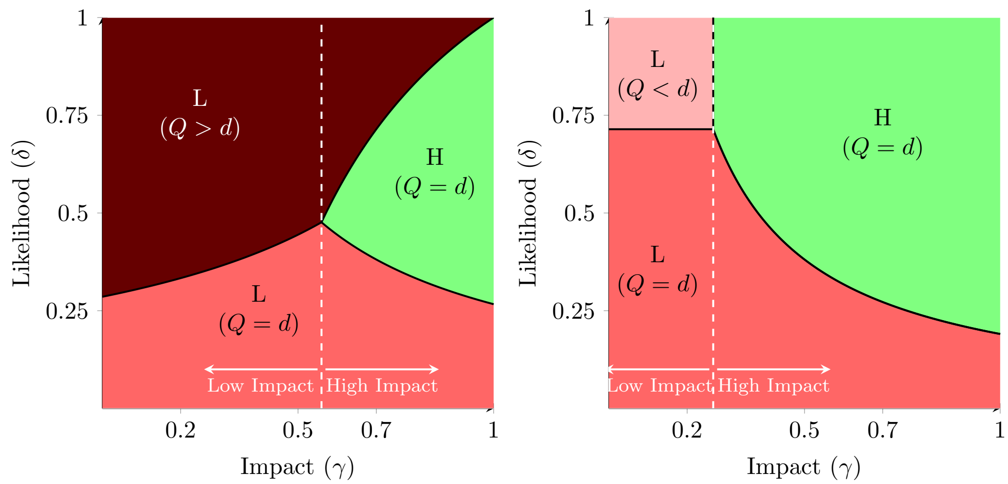
Proposition 3.1. *When sourcing from supplier L introduces potential supply disruption risk, the profit-maximizing strategy is to sole-source as follows:*

(1) Select supplier H and set $Q = Q_H = d$ *when* $\gamma_{SD} > \frac{pc_\Delta}{c_H(p-c_L)}$ *and* $\frac{c_\Delta}{\gamma_{SD}(p-c_L)} < \delta_{SD} \leqslant \frac{\gamma_{SD}c_H - c_\Delta}{\gamma_{SD}c_L}$*;*

(2) Select supplier L and

(a) set $Q = Q_L = d$ *when* $\gamma_{SD} > \frac{pc_\Delta}{c_H(p-c_L)}$ *and* $\delta_{SD} \leqslant \frac{c_\Delta}{\gamma_{SD}(p-c_L)}$*, or* $\gamma_{SD} \leqslant \frac{pc_\Delta}{c_H(p-c_L)}$ *and* $\delta_{SD} \leqslant \frac{c_L}{p-\gamma_{SD}(p-c_L)}$*;*

(b) set $Q = Q_L = d/(1-\gamma_{SD})$*, otherwise.*



(a) Supply Disruption Risk (SD) (b) Responsibility Violation Risk (RV)

Figure 3.1: Buyer's Optimal Sourcing Strategy under SD and RV

Proposition 3.1 specifies how the optimal sourcing strategy varies based on the likelihood (δ_{SD}) and impact (γ_{SD}) of the supply disruption. Panel (a) of Figure 3.1 illustrates the general structure. From this figure, we see that when the impact is lower than a certain threshold ($\gamma_{SD} \leqslant \frac{pc_\Delta}{c_H(p-c_L)}$), supplier L is the dominant choice, although the order quantity may change depending on the likelihood level. For low likelihood, it is optimal to simply order the demand level. However, when the likelihood increases beyond a threshold ($\delta_{SD} > \frac{c_L}{p-\gamma_{SD}(p-c_L)}$), it becomes advantageous to order more than the demand level in order to counteract the increased chance of yield loss.

The recommended sourcing strategy differs when the impact is high ($\gamma_{SD} > \frac{pc_\Delta}{c_H(p-c_L)}$). Now, supplier H emerges as the dominant choice in an interior region for moderate likelihood levels, while supplier L is still preferred otherwise. In the high likelihood region in which supplier L is preferred, it is again advantageous to order more than the demand level to counteract the potential yield loss. These insights are formalized in the following proposition.

Proposition 3.2. *An increase in the likelihood of supply disruption influences the buyer's optimal sourcing strategy as follows:*

(1) Low impact condition ($\gamma_{SD} \leqslant \frac{pc_\Delta}{c_H(p-c_L)}$): the buyer always chooses supplier L but the order quantity Q_L^* increases from d to $d/(1-\gamma_{SD})$ as δ_{SD} crosses the threshold $\frac{c_L}{p-\gamma_{SD}(p-c_L)}$ from below;

(2) High impact condition ($\gamma_{SD} > \frac{pc_\Delta}{c_H(p-c_L)}$): the buyer switches from supplier L ($Q_L^* = d$) to supplier H ($Q_H^* = d$) when δ_{SD} crosses the threshold $\frac{c_\Delta}{\gamma_{SD}(p-c_L)}$ from below and then back to supplier L ($Q_L^* = d/(1-\gamma_{SD})$) when δ_{SD} further increases above the threshold $\frac{\gamma_{SD}c_H - c_\Delta}{\gamma_{SD}c_L}$.

3.2.2 Normative Benchmark for Responsibility Violation Risk

Next, consider the case where sourcing from supplier L introduces the possibility of a responsibility-related violation. As highlighted in section 3.1, such violations may include the use of child labor or the exploitation of natural resources. This type of supplier-induced risk can also be characterized by its likelihood $\delta_{RV} \in (0,1)$ and its potential impact $\gamma_{RV} \in (0,1]$. However, the structure of a responsibility violation is different from the supply disruption case. Specifically, while a supply disruption influences the quantity of products for sale, a responsibility violation has the potential to influence customer demand. Following Guo et al. (2016), we assume that if a responsibility violation comes to light, a fraction (γ_{RV}) of customers will boycott the products sourced by the buyer and take their business elsewhere, i.e., the demand faced by the buyer is reduced to $(1-\gamma_{RV})d$. From the customer's perspective, it is often difficult to directly discern the specific supplier for a given product unit. Therefore, we assume that the fraction of customers boycotting the firm's product does not depend on the actual quantity of products sourced from supplier L, but only on whether or not the buyer sourced from that supplier (i.e., if supplier L is not awarded any business, then there is no risk of a responsibility violation for the buyer). The buyer's expected profit

π_{RV} in this case is as follows:

$$\begin{aligned}\pi_{RV}(Q_L, Q_H) = &(1 - \mathbb{1}(Q_L > 0)\delta_{RV})\, p \min\{Q_L + Q_H, d\} + \\ &\mathbb{1}(Q_L > 0)\delta_{RV} p \min\{Q_L + Q_H, (1-\gamma_{RV})d\} - Q_L c_L - Q_H c_H,\end{aligned} \tag{3.2}$$

where $\mathbb{1}(X)$ is an indicator function that takes the value of 1 if X is true and 0 otherwise. Proposition 3.3 characterizes the profit-maximizing sourcing strategy for a buyer under RV.

Proposition 3.3. *When sourcing from supplier L introduces potential responsibility violation risk, the profit-maximizing strategy is to sole-source as follows:*

(1) Select supplier H and set $Q = Q_H = d$ when $\gamma_{RV} > \frac{c_\Delta}{p-c_L}$ and $\delta_{RV} > \frac{c_\Delta}{\gamma_{RV} p}$;

(2) Select supplier L and

(a) set $Q = Q_L = d$ when $\gamma_{RV} > \frac{c_\Delta}{p-c_L}$ and $\delta_{RV} \leqslant \frac{c_\Delta}{\gamma_{RV} p}$, or $\gamma_{RV} \leqslant \frac{c_\Delta}{p-c_L}$ and $\delta_{RV} \leqslant \frac{p-c_L}{p}$;

(b) set $Q = Q_L = (1-\gamma_{RV})d$, otherwise.

Panel (b) of Figure 3.1 illustrates the buyer's optimal sourcing strategy when faced with RV. Comparing the two panels in the figure, we see that under both risk types, an impact threshold separates the high- and low-impact regions, with the threshold under RV smaller. Within each region, likelihood further determines the buyer's optimal sourcing strategies. Supplier H only becomes an active choice when the impact is high. When the impact is low, supplier L is always optimal, and the order quantity may deviate from demand d if the likelihood is sufficiently high. The direction of this deviation differs across the two risk types: the order quantity is set lower than d under RV to ensure there is no leftover inventory if a responsibility violation occurs, while it is set higher than d under SD to ensure there is sufficient inventory to meet demand in case of a supply disruption. Proposition 3.4 further summarizes these insights specific to RV.

Proposition 3.4. *An increase in the likelihood of responsibility violation influences the buyer's optimal sourcing strategy as follows:*

(1) Low impact condition ($\gamma_{RV} \leqslant \frac{c_\Delta}{p-c_L}$)*: the buyer always chooses supplier L but the order quantity* Q_L^* *decreases from* d *to* $(1-\gamma_{RV})d$ *as* δ_{RV} *crosses the threshold* $\frac{p-c_L}{p}$ *from below;*

(2) High impact condition ($\gamma_{RV} > \frac{c_\Delta}{p-c_L}$)*: the buyer switches from supplier L* ($Q_L^* = d$) *to supplier H* ($Q_H^* = d$) *as* δ_{RV} *crosses the threshold* $\frac{c_\Delta}{\gamma_{RV} p}$ *from below.*

3.3 Behavioral Hypotheses

As we see in previous sections, the decision settings for SD and RV differ in multiple ways, and some of these differences lead to distinctive optimal sourcing strategies under the two risk types. In forming our behavioral hypotheses regarding how buyers make sourcing decisions under SD and RV, it is helpful to highlight the major differences between the decision settings for the two risk types and introduce some additional terminology. These differences can be organized by dimensions of *structure* and *context*, as summarized in Table 3.1.

Structure defines how the impact of the risky event influences the buyer's supply chain. For example, the risky event under SD influences product supply and is limited to only the focal supplier where the event occurs. We refer to this type of structure as supply-focal, where supply signifies the *domain* of the impact and focal denotes its *scope*. In contrast, the risky event under RV influences the demand domain and has a broader scope that crosses over to both suppliers. We refer to this structure as demand-cross.

Context reflects the nature of the risky event itself. Unlike structure, this characteristic does not alter the optimal sourcing strategy. Instead, it might influence the buyer's decisions through the framing effect. Under RV, the risky event involves a violation of business practices, which might evoke ethical consciousness. This reaction is unlikely under SD, where the risky event is attributed to a process disruption.

Table 3.1: Characteristics of the Decision Setting under SD and RV

	Supply Disruption (SD)	**Responsibility Violation (RV)**
Structure (Domain-Scope)	Supply-Focal	Demand-Cross
Context	Disruption	Violation

Recall our normative results indicate that sole-sourcing is optimal under both SD and RV, and the optimal supplier to source from varies based on the likelihood and impact levels. Based on the characteristics of the decision settings under the two risk types summarized in Table 3.1, our behavioral hypotheses examine to what extent actual buyer decisions deviate from these normative predictions. Specifically, we are interested in exploring: (i) Do buyers diversify? (ii) Do buyers' supplier preferences differ from the optimal solution?

3.3.1 Diversification Behavior

Prior research has identified diversification bias as a persistent behavioral phenomenon: people tend to diversify when multiple options are available to them (see, e.g., Read and Loewenstein 1995). Behavioral studies related to sourcing decisions often attribute buyers' tendency to choose more than one supplier when sole-sourcing is optimal to this general bias toward diversification (e.g., Gurnani et al. 2014). While we are likely to observe diversification in our setting as well, the more interesting question is how the propensity to diversify varies across SD and RV, given the structural and contextual differences we observe in Table 3.1.

First, we conjecture that the distinctive underlying *structures* under SD and RV may require different levels of cognitive processing. In the RV case, the two supply sources are interrelated, and the influence of violations at supplier L's site can spill over, since keeping supplier L in the supply base opens up the prospect of violations and the resulting loss of demand, regardless of the quantity sourced from that supplier. Reducing the amount sourced from L, unless completely down to zero, does not help curtail risk exposure. A sound understanding of this unique structure may help buyers recognize the "all-or-nothing" nature, pushing them to sole-source from either supplier H (to eliminate risk) or supplier L (to minimize the total procurement cost while bearing risk). In contrast, in the SD case, the influence is focal in nature, i.e., disruptions at supplier L do not influence production and quantity delivered by supplier H. Consequently, the two supply sources are independent, making the risk exposure proportional to the actual quantity sourced from supplier L. Given people's natural tendency to process information incrementally (e.g., Hogarth and Karelaia 2007), a better understanding of this linear risk structure, by itself, may not be helpful in pushing buyers under SD toward sole-sourcing.

Second, the different *contexts* under SD and RV are likely to lead to different affective reactions. Under RV, potential violations might induce moral judgment, since buyers' decisions have vital implications for the welfare of various stakeholders, including the supplier's employees who might be adversely influenced by the practices and customers who may be concerned about the firm's environmental and social conduct. Previous research suggests that moral judgment often involves, and can even be guided by, emotional responses (e.g., Rozin et al. 1999, Haidt 2001), and consequently, we expect the context of RV to evoke strong affective reactions. Since choosing supplier L under RV involves moral ambiguity, buyers' affective responses might prompt them to avoid doing business with supplier L. However, this aspect is not salient under SD because the influence of disruptions is purely economic. Hence, the context of SD is unlikely to trigger ethical judgment that pushes buyers toward avoiding supplier L. Thus, buyers under SD are more likely to split their orders between the two supplier candidates. Since forces from both the cognitive and affective aspects point to less diversification under RV, we hypothesize the following:

Hypothesis 3.1. *Buyers are less likely to exhibit diversification bias when faced with the risk of a responsibility violation relative to a supply disruption.*

3.3.2 Buyer Preference: Low- vs. High-cost Supplier

We next examine how buyers' supplier preference may vary across SD and RV, and how this behavior changes across scenarios where the normative theory identifies supplier H vs. supplier L as optimal. We are especially interested in the scenarios in which supplier H is identified as optimal, since it is a "win-win" sourcing strategy under RV: sole-sourcing from supplier H is not only economically optimal for the buyer, but also "socially optimal" from a stakeholder perspective.

When sourcing from supplier H is optimal, the influence of cognitive processing and affective reactions is congruent under RV. From a cognitive perspective, as previously discussed, a better understanding of the "all-or-nothing" risk that spills across the two suppliers under RV may help buyers overcome diversification bias and increase the rate of sole-sourcing. The increased tendency to sole-source also narrows the choice set to two alternatives, and we anticipate that this narrowing of the choice set will help buyers in correctly identifying the optimal supplier under RV relative to SD. From an affective perspective, buyers under RV might feel that retaining supplier L in the supply base is not justifiable on moral grounds. On the other hand, exclusively sourcing from supplier H helps strengthen their commitment to stakeholder welfare. These considerations will push them toward sole-sourcing from supplier H, especially among individuals who are more ethically conscious. However, under SD, whether or not to include supplier H in the mix involves only cost-benefit tradeoff considerations, without any ethical judgments. As a result, buyers under RV may have a higher propensity to commit to supplier H. Therefore, we formally hypothesize:

Hypothesis 3.2. *When it is optimal to sole-source from supplier H, buyers are more likely to correctly select the optimal supplier when faced with the risk of a responsibility violation relative to a supply disruption.*

When sourcing from supplier L is optimal, the influence of cognitive processing and affective reactions is incongruent under RV. From a cognitive perspective, the benefits resulting from a better understanding of the risk structure may help buyers to narrow down the choice set to two alternatives, resulting in an increased likelihood of correctly selecting the optimal supplier (i.e., supplier L) under RV. From an affective perspective, buyers faced with RV may exhibit a stronger aversion toward sourcing from supplier L since it involves the possibility of violating business practices and ethical standards and the low-cost supplier is actively involved and has direct control over the risky event (Sparanca et al. 1991). Based on the above discussion, we see that the forces from the cognitive and affective aspects point us in different directions with regard to the buyers' preferred choice of supplier when faced with RV, and it is not clear which of the two forces dominate. As a result, we have formulated the following competing hypotheses:

Hypothesis 3.3A. When it is optimal to sole-source from supplier L, buyers are more likely to correctly select the optimal supplier when faced with the risk of a responsibility violation relative to a supply disruption.

Hypothesis 3.3B. When it is optimal to sole-source from supplier L, buyers are less likely to correctly select the optimal supplier when faced with the risk of a responsibility violation relative to a supply disruption.

3.3.3 Influence of the Operating Environment

Having considered the potential for behavioral deviations with respect to diversification and supplier selection, we now examine how buyers' sourcing strategies vary as the underlying likelihood and impact levels change. From Propositions 3.2 and 3.4, we observe that the optimal strategy for a profit-maximizing buyer does not change in a continuous or incremental fashion, and this step-wise nature is not always intuitive. However, it is well-known from the judgment and decision-making literature that individuals often use intuition-based heuristics when making decisions (e.g., Tversky and Kahneman 1974). Furthermore, prior research shows that individuals often process relevant decision cues in an incremental fashion (e.g., Hogarth and Karelaia 2007) and use linear extrapolations that can substantially deviate from the theoretical predictions in non-linear systems, such as environments involving exponential growth (e.g., Wagenaar and Sagaria 1975). Our normative results suggest that the sourcing setting analyzed in this work is also a non-linear system. As such, we predict that when the likelihood changes, buyers will adjust their sourcing strategies in an incremental way under the influence of heuristic reasoning. Specifically, for small changes in likelihood, we postulate that buyers will apply minor tweaks to their sourcing strategy rather than making step-wise adjustments as the optimal strategy suggests. Given our previous argument that buyers are likely to diversify when faced with either risk type, such minor tweaks may manifest in the form of incremental adjustments to the orders allocated to the two suppliers. This behavioral tendency has different implications for scenarios with low vs. high impact levels. To more concretely construct our hypothesis, we describe likelihood changes in an increasing direction, but this does not imply that buyers face continuously increasing likelihood levels in reality or our experiment.

Recall that when the impact is low, the buyer's profit-maximizing strategy is to choose supplier L and adjust the order quantity (upward under SD and downward under RV) if the likelihood of a disruption or violation is above a certain threshold. Our behavioral prediction is that individuals will allocate more of their orders to supplier H whenever the likelihood increases, rather than follow the normative strategy of tweaking the order quantity from L.

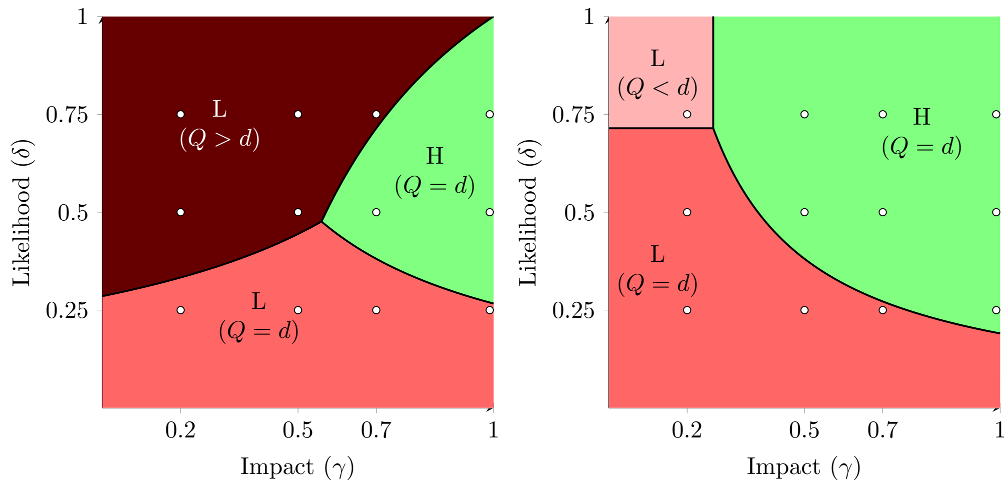
On the other hand, when the impact is high, a profit-maximizing buyer needs to consider different suppliers as the likelihood increases (see the high impact condition in Propositions 3.2 and 3.4). Our behavioral prediction is that buyers will react in an optimal way directionally by sourcing more from supplier H, but they will do so incrementally rather than switching altogether. In addition, buyers may equate higher likelihood with higher uncertainty, failing to realize the benefit of exclusively sourcing from supplier L when the likelihood is high under SD. Synthesizing the above arguments, we formally hypothesize the following:

Hypothesis 3.4. *Buyers will increase the proportion of orders awarded to supplier H whenever the likelihood of a supply disruption or responsibility violation increases, regardless of the impact level.*

3.4 Experimental Design

We used a behavioral experiment to test our hypotheses, with participants assuming the role of a buyer making sourcing decisions within the settings described in section 3.2. Participants were randomly assigned to one of two treatments corresponding to either supply disruption or RV. The main task for participants was to decide how much to order from each of the two suppliers in a series of decision scenarios, with each scenario varying in terms of the levels of likelihood (δ_i; three levels: 0.25, 0.5, and 0.75) and impact (γ_i; four levels: 0.2, 0.5, 0.7, and 1). Figure 3.2 illustrates how the 12 scenarios map to normative predictions under each risk type. Every participant made decisions for all 12 scenarios with two repetitions, and the 24 rounds were presented in a random sequence. Data from the first repetition were utilized for the main analysis, while data from the second repetition were used to test the robustness of our results. We fixed $c_H = \$30$, $c_L = \$18$, $p = \$63$, and $d = 100$ throughout the experiment. Our calibrations of the cost and risk levels are comparable with prior research (e.g., Gurnani et al. 2014). The experiment was run on the SoPHIE software platform (Hendriks 2012). Screenshots are provided in the Appendix.

We recruited participants from the Amazon Mechanical Turk (MTurk) subject pool, which has been used in a variety of behavioral studies (e.g., Berinsky et al. 2012), including behavioral operations (e.g., Lee et al. 2018). Our participants were limited to MTurk workers in the U.S. who previously completed at least 500 tasks and had an overall approval rating of at least 95%. In total, 217 MTurk workers ($N_{male} = 115$,



(a) Supply Disruption (SD) (b) Responsibility Violation (RV)

Figure 3.2: Mapping of Decision Scenarios to Normative Predictions under SD and RV

$M_{age} = 39.45$) completed all of the required activities, with 108 participants randomly assigned to the SD treatment and the other 109 to the RV treatment. Participants began by reading instructions, answering a set of quiz questions to make sure they understood the setting, and completing three practice rounds to familiarize themselves with the process and interface before proceeding to the main task. After completing each scenario, participants saw the associated outcome (i.e., whether a supply disruption or responsibility violation occurred, depending on which treatment they were assigned to) and corresponding profit. After completing the last scenario, participants answered a set of survey questions. The final payment consisted of a flat participation fee and a performance-based payment that was associated with each participant's average profit across all rounds of the game. The average payment per participant was \$4.07.

3.5 Experimental Results

Before analyzing the data, we removed data points corresponding to participants who exhibited one of the following outlier behaviors in at least one scenario: (1) set both Q_L and Q_H to zero (i.e., $Q = 0$), and (2) set $Q > 3330$, which is more than 10 times the highest possible optimal order quantity. Applying these exclusion criteria reduced the sample size to 107 for the SD treatment and 105 for the RV treatment, removing five participants in total. The main analysis is based on participant responses from the first repetition of the 12 decision scenarios, as indicated in the prior section. A robustness analysis of data from the second repetition confirms the key results of our main analysis.

3.5.1 Diversification Behavior

Before testing Hypothesis 3.1, we first compute the proportion of buyers who diversify (i.e., source from both suppliers) under each decision scenario. Figure 3.3 reports the corresponding 95% confidence intervals, with the averages ranging from 40% to 80%. While some diversification clearly exists in all scenarios, the propensity to diversify appears to be lower under RV relative to SD.

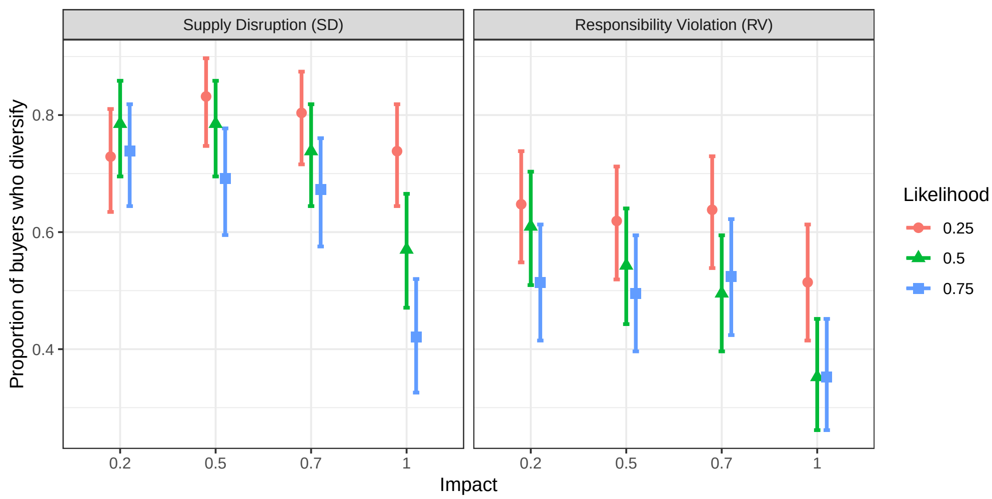


Figure 3.3: 95% Confidence Intervals of the Proportion of Buyers Who Diversify

To more rigorously measure the influence of risk type on diversification, we utilize logistic regressions, with the dependent variable $Diversification$ capturing whether or not the buyer diversifies. Our primary independent variable of interest, $RiskTypeR$, is coded as 1 for the RV treatment and 0 otherwise. We use clustered standard errors at the participant level throughout our analysis. Table 3.2 reports the results. In Model 2, the coefficient of $RiskTypeR$ is negative and significant ($p < 0.001$), with the odds of diversification decreasing by $1 - e^{-0.825} = 56.18\%$ under RV. The corresponding average marginal effect is a 17.98 percentage point reduction in the probability of diversification under RV relative to SD. These results support Hypothesis 3.1.

Table 3.2: Logistic Regression Results on Diversification

	(1)	(2)
Constant	1.677^{***}	2.573^{***}
	(0.330)	(0.379)
Round		-0.028^{***}
		(0.007)
$\gamma_i = 0.5$		-0.048
		(0.087)
$\gamma_i = 0.7$		-0.128
		(0.086)
$\gamma_i = 1$		-0.807^{***}
		(0.104)
$\delta_i = 0.5$		-0.389^{***}
		(0.087)
$\delta_i = 0.75$		-0.642^{***}
		(0.102)
RiskType	-0.788^{***}	-0.825^{***}
	(0.208)	(0.219)
Observations	2,544	2,544
Log Likelihood	-1646	-1592
AIC	3297	3199

Note: $^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

3.5.2 Buyer Preference: Low- versus High-cost Supplier

We next examine buyers' sourcing strategies in terms of how orders are allocated across the two suppliers. Figure 3.4 contains a set of histograms displaying the mean proportion of orders awarded to supplier H, i.e., Q_H/Q, under the two risk types. The top panel corresponds to scenarios in which supplier H is the optimal choice from a profit-maximizing perspective. The percentages of instances in which buyers choose to sole-source from supplier H (i.e., align with the optimal policy) are above 40% under both risk types, with the percentage under RV appearing higher. To rigorously test the influence of risk type on buyer behavior, we perform a logistic regression on the likelihood of correct sole-sourcing, with the results reported in Table 3.3. Model 2 indicates that buyer behavior is significantly different across the two risk types ($p < 0.01$), with the odds of committing exclusively to supplier H higher by $e^{0.680} - 1 = 97.38\%$ under RV. The corresponding average marginal effect is a 16.18 percentage point increase in the probability of correctly sole-sourcing from supplier H under RV relative to SD. These results provide support for Hypothesis 3.2.

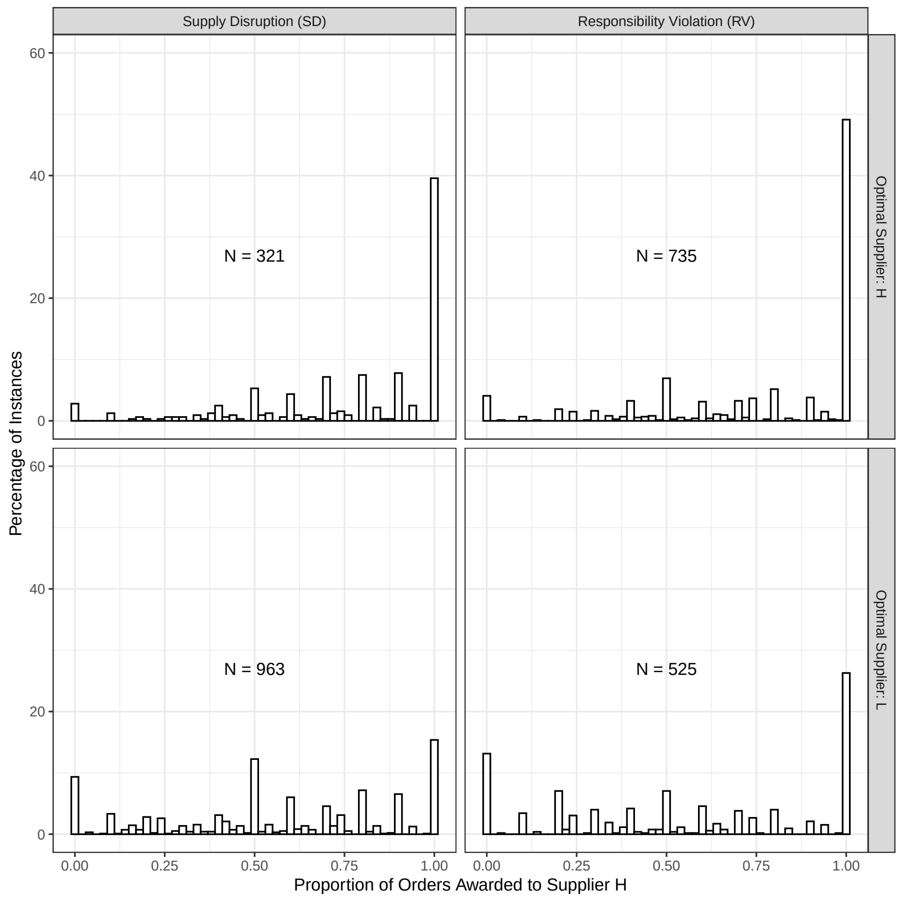


Figure 3.4: Histograms of the Proportion of Orders Awarded to Supplier H (Q_H/Q)

The bottom panel of Figure 3.4 illustrates the scenarios in which supplier L is the optimal choice. From the figure, we see that in less than 20% of the instances, buyers sole-source from supplier L, and this proportion is quite comparable across the two risk types. Model 4 in Table 3.3 confirms that the probability of correctly selecting the optimal supplier (i.e., supplier L) is indeed similar across the two risk types, since the coefficient of $RiskTypeR$ is not statistically different from 0. This implies that neither Hypothesis 3.3A nor Hypothesis 3.3B is supported.

Table 3.3: Logistic Regression Results on Correct Sole-Sourcing

	OptSupplier = H		OptSupplier = L	
	(1)	(2)	(3)	(4)
Constant	-0.812^{*}	-2.660^{***}	-2.656^{***}	-1.209^{*}
	(0.358)	(0.506)	(0.443)	(0.530)
Round		0.010		0.009
		(0.011)		(0.016)
$\gamma_i = 0.5$				-1.120^{***}
				(0.229)
$\gamma_i = 0.7$		-0.021		-1.253^{***}
		(0.110)		(0.226)
$\gamma_i = 1$		0.682^{***}		-1.259^{***}
		(0.136)		(0.365)
$\delta_i = 0.5$		0.926^{***}		-0.729^{***}
		(0.179)		(0.140)
$\delta_i = 0.75$		1.161^{***}		-1.216^{***}
		(0.186)		(0.172)
RiskType	0.388^{+}	0.680^{**}	0.384	0.010
	(0.224)	(0.243)	(0.280)	(0.301)
Observations	1,056	1,056	1,488	1,488
Log Likelihood	-724.8	-706	-503.3	-475.1
AIC	1454	1426	1011	966.1

Note: Supplier H is the optimal option only for $\gamma_i \geqslant 0.5$. Hence, the baseline for Model 2 is $\gamma_i = 0.5$ instead of $\gamma_i = 0.2$.
$^{+}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

3.5.3 Influence of the Operating Environment

Hypothesis 3.4 predicted that buyers will respond to changes in likelihood by incrementally adjusting order allocation between the two suppliers instead of making step-wise changes, as the normative solution suggests. Figure 3.5 illustrates how buyers adjust the proportion of orders awarded to supplier H (i.e., Q_H/Q) as a function of likelihood for different impact levels and risk types. From the figure, we see that Q_H/Q increases monotonically with likelihood, following either a linear or a concave trend, with higher impact invoking greater concavity. These general trends do not appear to vary significantly across the two risk types, and more importantly, there is no evidence of the step-wise changes predicted by our normative models.

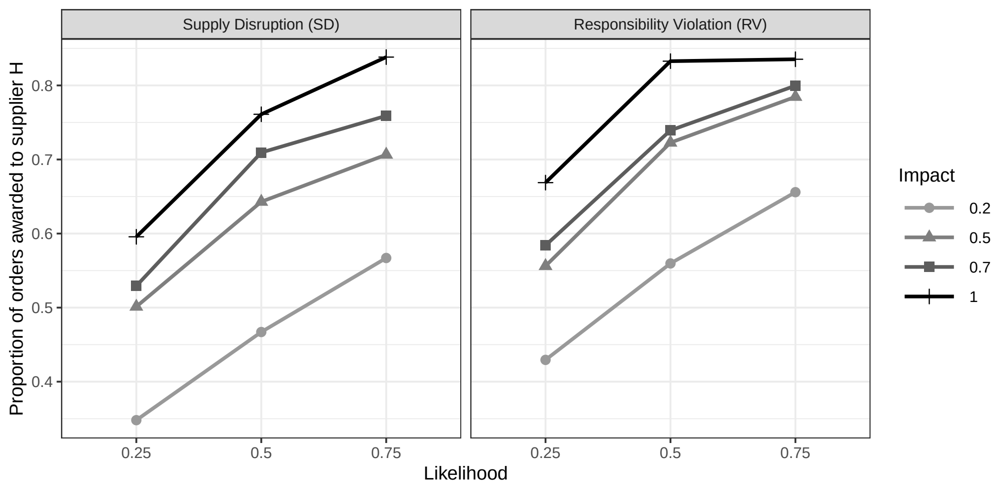


Figure 3.5: Proportion of Orders Awarded to Supplier H (Q_H/Q)

To test our hypothesis regarding buyers' adjustment behavior, we use OLS (ordinary least squares) regression models, with Q_H/Q as the dependent variable. Table 3.4 summarizes the results. As we see from Models 3 and 6, when likelihood increases from 0.25 to 0.5, the proportion of orders awarded to supplier H increases by 15 percentage points, with an additional increase of 6 to 7 percentage points as likelihood increases further from 0.5 to 0.75. This general pattern also holds when we examine the subsamples corresponding to low and high impact levels in Models 1-2 and 4-5. These results support Hypothesis 3.4.

Another implication of the behavior suggested by Hypothesis 3.4 is that buyers' sourcing patterns may not be consistent with the interesting strategy that emerged in our analytical results when likelihood is high (see Propositions 3.2 and 3.4). In a subset of that region, it is advantageous to stick with supplier L, but the order quantity

Table 3.4: OLS Regression Results on the Proportion of Orders Awarded to Supplier H for Different Impact Levels

	Supply Disruption Risk			Responsibility Violation Risk		
	Low-Impact	High-Impact	All	Low-Impact	High-Impact	All
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.412***	0.558***	0.321***	0.449***	0.577***	0.404***
	(0.024)	(0.023)	(0.031)	(0.030)	(0.024)	(0.030)
Round	0.002	0.001	0.002	−0.002	0.003+	0.003+
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)
$\gamma_i = 0.5$			0.156***			0.141***
			(0.027)			(0.027)
$\gamma_i = 0.7$			0.205***			0.161***
			(0.029)			(0.029)
$\gamma_i = 1$			0.272***			0.232***
			(0.034)			(0.032)
$\delta_i = 0.5$	0.131***	0.173***	0.152***	0.129***	0.164***	0.155***
	(0.019)	(0.024)	(0.018)	(0.031)	(0.024)	(0.021)
$\delta_i = 0.75$	0.211***	0.236***	0.224***	0.226***	0.205***	0.210***
	(0.024)	(0.027)	(0.022)	(0.041)	(0.027)	(0.026)
Participant Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	642	642	1284	315	945	1260
R^2	0.132	0.213	0.270	0.165	0.148	0.202
Adjusted R^2	0.128	0.209	0.267	0.157	0.146	0.199

Note: $^+p < 0.1$; $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$

should be set lower than d when faced with RV and higher than d when faced with SD. To provide a view of buyers' actual sourcing behavior in this region, we highlight one decision scenario ($\gamma_i = 0.2$ and $\delta_i = 0.75$) where adjusting Q away from d is optimal for both risk types. Table 3.5 shows that a majority of buyers set $Q = d$, with more failing to adjust when faced with RV than when faced with SD (χ^2 test, $\chi^2(1) = 15.1020$, $p = 0.0001$; similar results hold when using Fisher's Exact Test). Among those who adjust their order quantity when faced with SD, more appear to do so in the correct direction ($Q > d$). A binomial test rigorously confirms this assertion ($p < 0.0001$). The few buyers who adjust their order quantities when faced with RV do not consistently adjust in the correct direction (in this case, $Q < d$; $p = 0.7905$). These results suggest that buyers are generally unaware of the benefit of adjusting Q downward when faced with RV but might recognize, at least to a certain degree, the benefit of adjusting Q upward when faced with SD.

Table 3.5: Buyers' Order Quantity in the Selected Decision Scenario ($\gamma_i = 0.2$ and $\delta_i = 0.75$)

Risk Type	N	$N_{Q<d}$	$N_{Q=d}$	$N_{Q>d}$	$Q < d$ (%)	$Q = d$ (%)	$Q > d$ (%)
SD	107	6	68	33	5.6	63.6	30.8
RV	105	6	91	8	5.7	86.7	7.6

3.6 Post-Hoc Analysis of Expected Profit Implications

Our experimental data provide opportunities to investigate how buyers' actual expected profits compare relative to normative predictions, which in turn brings to light some potential improvement strategies. As a benchmark, it is helpful to first examine how the optimal profit, resulting from the sourcing strategies defined in Propositions 3.1 and 3.3, varies across scenarios. Figure 3.6 illustrates these benchmarks through a series of dashed lines. Under RV (Panel (b)), optimal profit decreases with the likelihood of a violation, which is consistent with intuition. In contrast, under SD (Panel (a)), the optimal profit does not monotonically decrease with likelihood under some scenarios. For example, as the likelihood of a disruption increases from 0.5 to 0.75, buyers' optimal profit increases. This is because in those scenarios, as the likelihood of a disruption increases beyond a moderate level, the uncertainty faced by the buyer actually decreases. As such, the buyer can more effectively counteract the likely threat of a supply disruption by inflating the order quantity, since the chance of overstocking is low at high likelihood levels.

Buyers' actual profits, as calculated from our experimental data, are illustrated in Figure 3.6 through a series of solid lines. From the figure, we see that there is a considerable gap between the normative and actual profits for each scenario, with significantly larger gaps under RV (26.91% for each participant on average). The percentage gap in profits under SD is somewhat lower but is still substantial at 14.13%. To obtain a better understanding of the difference in profit gaps across the two risk types, we plot a set of histograms in Figure 3.7, displaying the profit gap by risk type. When it is optimal to sole-source from supplier H (top panel), roughly 20% of the participants' ordering behavior is consistent with the optimal strategy under each risk type. However, more participants incur higher losses under RV, leading to a larger mean gap when compared

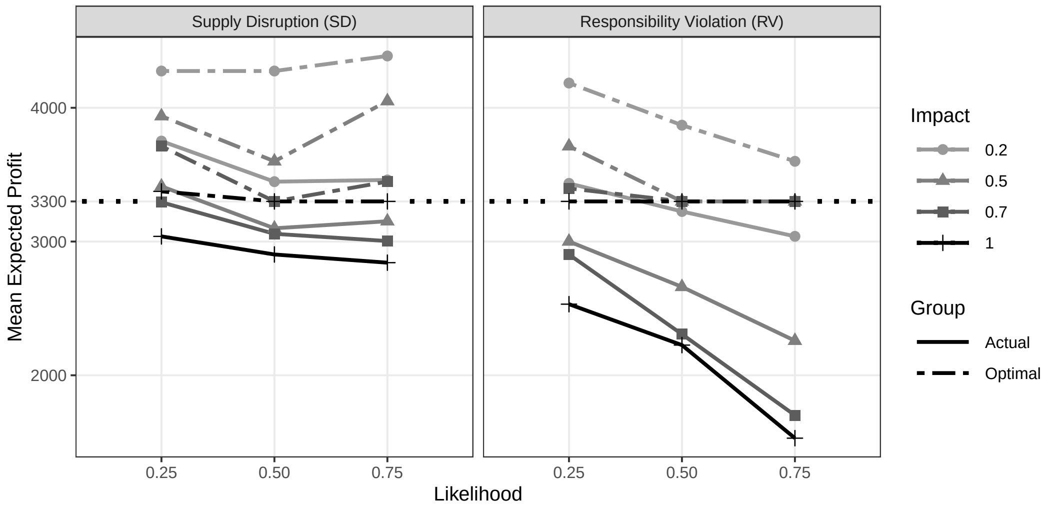


Figure 3.6: Comparison of Optimal and Actual Expected Profits under Different Decision Scenarios

with the supply disruption case. In contrast, when it is optimal to sole-source from supplier L (bottom panel), participants have similar profit gaps across the two risk types. These comparisons indicate that the scenarios where it is optimal to source from supplier H present particular challenges to buyers faced with the risk of a responsibility violation. Next, we examine one specific strategy that might help to address this issue.

The horizontal dotted reference line in Figure 3.6 shows the profit (= \$3300) if the buyer always sole-sources from supplier H (the risk-free option) with $Q_H = d$. From the figure, we see that sourcing exclusively from the high-cost supplier is an effective strategy for the buyer under RV, especially when the likelihood and impact of the risk are moderate to high. In such settings, sourcing exclusively from supplier H results in optimal or near-optimal performance. In settings characterized by low likelihood and impact, sourcing exclusively from supplier H still yields substantial improvements over the actual sourcing decisions made by participants in our experiments, resulting in a total profit increase of nearly 52.87%. Under SD, sourcing exclusively from supplier H outperforms the participants' sourcing strategies, resulting in an average profit increase of 14.31%. However, sole-sourcing from supplier H still leads to a 10.92% loss relative to the optimal profits.

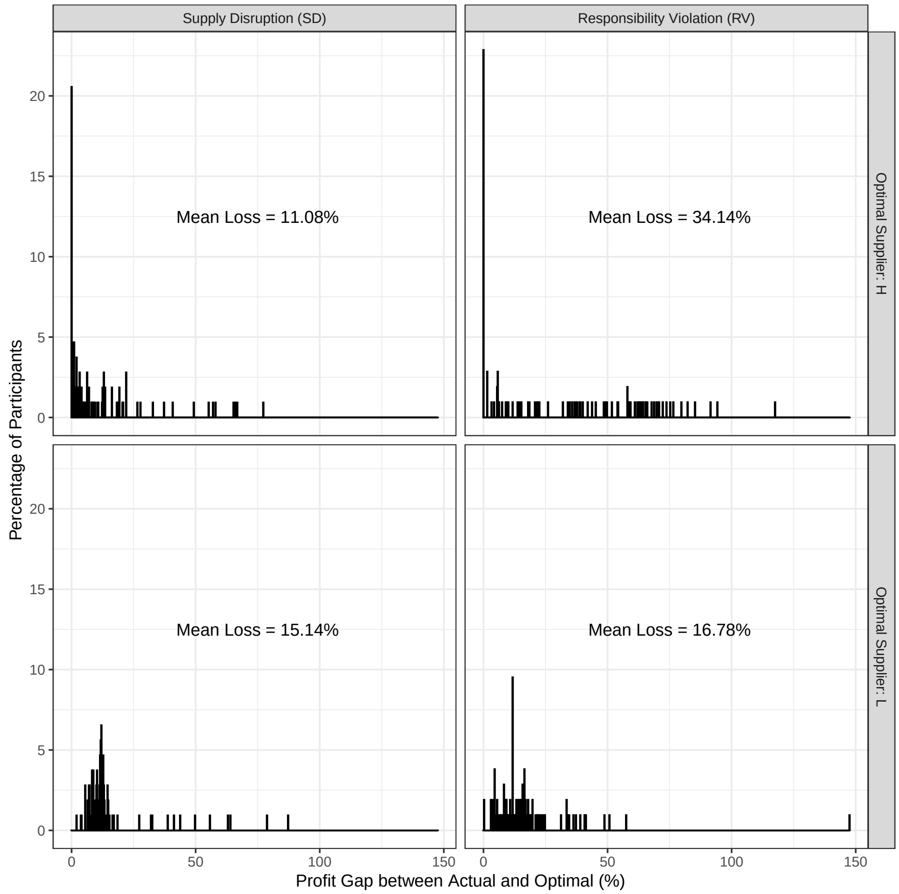


Figure 3.7: Histograms of the Profit Gap between Actual and Optimal (%)

3.7 Discussion and Conclusions

This study presents a comparative framework to evaluate buyers' sourcing decisions under different types of supplier-induced risks. Our behavioral theories argue that the problem strutures and decision contexts are different under the two risk types, eliciting different cognitive processing and affective reactions, which in turn lead to different ordering behaviors across SD and RV. We find that buyers' sourcing decisions do differ under supply disruption versus RV in terms of the extent of diversification and the probability of selecting the optimal supplier. Although many buyers diversify, in contrast to the normative recommendation of sole-sourcing, we find that buyers diversify less when faced with RV relative to SD. Furthermore, buyers under RV are more likely to sole-source from the profit-maximizing supplier when that supplier is the less risky option.

Our normative results in Propositions 3.2 and 3.4 indicate that when the likelihood of a disruption or violation increases, buyers may find it advantageous to change total order quantities as well as their supply source. In our experiment, we observe that buyers adjust total order quantities differently across the two risk types. Specifically, buyers facing RV are more likely to anchor their order quantity on demand and fail to realize that adjusting their order quantity downward may be an effective strategy to avoid overstocking. In contrast, a larger proportion of buyers facing SD seem to recognize that adjusting the total order quantity upward may be an effective strategy to combat the possibility of understocking. Future research could investigate whether such difficulty in making downward adjustments in sourcing decisions is connected with managers' similar behavior in other operations management domains such as inventory management (e.g., Zhang and Siemsen 2019).

Although buyers set total order quantities in different ways, their adjustments in order allocation to the two suppliers do not vary significantly across the two risk types when the operating environment changes. This pattern implies that buyers may be using a general heuristics-based approach when evaluating cost-risk tradeoffs, even though the underlying risks are fundamentally different in nature. This empirical observation deserves greater attention, since risk management tactics that are useful in tackling SD may be less effective (or even detrimental) in addressing RV. Based on a normative perspective, Guo et al. (2016) urge buyers to reevaluate their sourcing strategies when the nature of the risk changes. Our study further underscores the importance of developing a risk-type-specific sourcing strategy from a behavioral perspective.

In terms of expected profit, our analysis reveals that buyers leave more on the table when faced with RV, especially in scenarios where sole-sourcing from the high-cost supplier is the optimal strategy. This finding is striking, because buyers under RV sole-source more and have a higher tendency to select the high-cost supplier. A closer look at the distribution of the profit gaps in these scenarios reveals that buyers who dual-source incur larger losses more frequently under RV. This result suggests that one effective approach to narrowing the overall performance gap for buyers facing RV might be to commit to sole-sourcing from the high-cost supplier and not engage in dual-sourcing under such scenarios.

Our study has limitations that may serve as avenues for future work. First, our parsimonious setup, with the potential supply base consisting of one risky supplier and one risk-free supplier, allows for a clean comparison across the two risk types. However, researchers may find it worthwhile to explore sourcing behavior in more complex settings involving other combinations of risk profiles, such as when sourcing from either supplier introduces some risk or when either likelihood or impact information is unavailable (i.e., uncertainties). Second, our research focuses on investigating supplier selection and order quantity decisions, which could serve as a building block for future research related to other strategic decisions, such as mitigation or contingency plans made by buyers to address different supplier-induced risks (e.g., Tomlin 2006, Speier et al. 2011).

Chapter 4

Study 2: Supply Disruption vs. Responsibility Violation Risks: The Influence of Structure and Context

4.1 Introduction

Study 1 revealed that participants' ordering behaviors under supply disruption risk (SD) and responsibility violation risk (RV) are significantly different. In this study, we aim to delve deeper into the characteristics of decision settings of the two risk types and disentangle the effects of risk *structure* (i.e., whether a risk influences the supply or demand side of the supply chain, and whether the influence is focal to the impacted supplier or crosses over to the supply base) and *context* (i.e., whether the risky event is a process disruption or business practice violation). We introduce three new treatments for our behavioral experiments based on our risk taxonomy in Study 1. Comparing these new treatments against the two main treatments allows us to better understand the underlying driving forces and evaluate their relative importance in influencing buyers' sourcing decisions.

Another important goal of this study is to replicate the results of Study 1 using a different participant pool with management experience to explore the potential influence of management experience. In addition, we carefully modified our experimental design to reduce potential difficulties, including providing an optional decision-support tool to help calculate profit with different order quantities under consideration. We address the following research questions: (1) Are the main insights revealed in Study 1 robust to managerial experience and the assistance of decision support? (2) What structure and context characteristics drive buyers' ordering behavior? (3) How do buyers' sourcing strategies influence their profit performance?

Our experimental results reveal that the behavioral pattern we observe in Study 1 with respect to the differences under SD and RV also appears after we switch to a participant pool with managerial experience. In addition, a considerable portion of the differences between buyers' ordering behavior under SD and RV can be attributed to their different risk structures, especially their scope (i.e., whether the influence is focal to the low-cost supplier only or crosses over to the high-cost supplier). When facing a risk with cross-supplier influence, participants diversify less and are more likely to correctly sole-source from the high-cost supplier. In contrast, risk context plays a more limited role. Furthermore, our analysis of the influence of buyers' sourcing strategies on expected profit confirms that diversification reduces profit performance under both risk types. When considering which one of the two supplier candidates to sole-source from, buyers will be better off if they err on the side of sole-sourcing from the high-cost supplier. Individual differences related to cognitive and affective influence are also explored.

The remainder of the chapter is organized as follows: In section 4.2, we describe the experimental design of Study 2. In section 4.3, we discuss the replication results regarding buyers' sourcing strategies under SD and RV. To further disentangle the differences between the two risk types, we assess the effects of structure and context in section 4.4. We continue our analysis in section 4.5 by examining the performance implications of different sourcing strategies and identify potential individual attributes that are associated with buyers' strategy adoption. Finally, in section 4.6, we conclude with a discussion of the research implications, highlighting theoretical and managerial contributions and identifying possible future research directions.

4.2 Experimental Design

In this section, we begin by describing how the overall experimental design of Study 2 compares with that of Study 1. Next, we provide detailed information on how we design the treatments to help us replicate the results in Study 1 and further disentangle the effects of structure and context characteristics.

4.2.1 Changes in Experimental Design Relative to Study 1

The sourcing task and decision scenarios (i.e., the within-subject treatments of likelihood and impact levels) in this study follow our design in Study 1. However, there are three key differences.

First, we used a different participant pool. We recruited participants from the Prolific platform (Palan and Schitter 2018), which has been used in behavioral studies in a variety of fields, including supply chain management (e.g., DuHadway et al. 2018). In addition to the requirement of living in the U.S. and having completed at least 500 studies with an overall approval rate of at least 95%, we included one additional screening criterion to limit participants to those who have management experience.

Second, we modified several elements of our experimental design to further improve participants' understanding of the task environment and increase their incentives. Importantly, we added an optional decision-support tool for participants to calculate sales quantity and profit outcomes of order quantities under consideration to facilitate decision-making. In addition, we made a series of minor adjustments. Specifically, we updated the quiz questions to improve clarity; we increased the number of practice rounds from three to five to allow participants more time to familiarize themselves with the task; we reduced the number of rounds of the sourcing task from 24 to 12 (i.e., from 2 repetitions to 1 repetition) to reduce potential fatigue and dilution of incentives.

Third, our experimental research involves a total of five treatments, with participants randomly assigned to only one of them. These five treatments include the SD and RV treatments from Study 1 and three additional treatments designed to disentangle structure and context characteristics, which we detail below.

4.2.2 Design of Treatments

The results from Study 1 demonstrate that participants' ordering behaviors under SD and RV are significantly different with respect to diversification and correct sole-sourcing. To better understand the driving forces behind these results, we return to the fundamental differences between the two risk types that informed our behavioral hypotheses. We conjectured that buyers facing RV would resort to different levels of diversification and correct sole-sourcing for two reasons. First, under RV, the risk structure has a broader scope, crossing over to both suppliers. This crossover effect leads to an "all-or-nothing" nature, which may propel buyers to sole-source from H to eliminate risk or sole-source from L to minimize cost. Second, RV presents a context under which buyers face the prospect of violating business practices, which may trigger more affective responses. Consequently, buyers are likely to have a higher tendency to avoid doing business with L because of moral ambiguity. In this study, we disentangle the effects of structure (i.e., domain and scope) and context using three additional treatments that involve a systematic variation of these characteristics. These treatments were designed with careful consideration of their practical relevance, in addition to their ability to allow us to better understand the underlying driving forces and their relative importance in terms of influencing buyers' sourcing strategies.

As stated above, in Study 2, we introduce three additional treatments corresponding to supplier-induced risks that involve different combinations of structural and contextual characteristics. The three risk treatments are summarized and compared with SD and RV in Table 4.1. We discuss each of them in detail below.

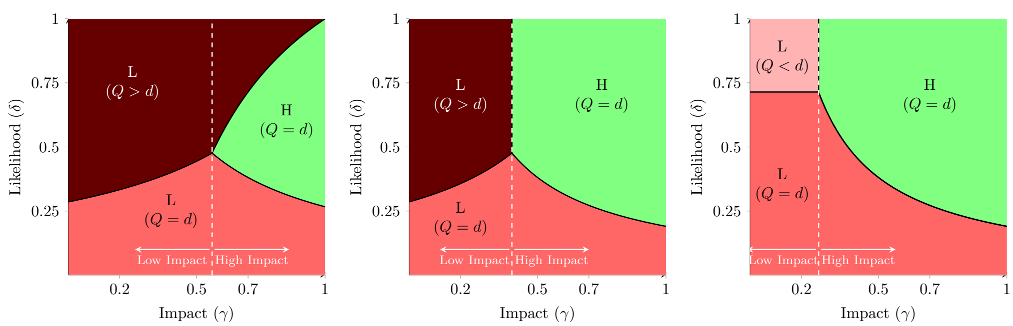
Table 4.1: Characteristics of the Decision Setting under Different Treatments

Treatment	**Supply Disruption (SD)**	**Safety Violation (SV)**	**Contamination Disruption (CD)**	**Reputation Disruption (RD)**	**Responsibility Violation (RV)**
Treatment Situation	Machine break-down	Building safety regulation violation	Product contamination	Reputation damage due to other products' quality problems	Labor regulation violation
Number of Participants	102	112	109	103	105
Structure (Domain-Scope)	Supply-Focal	Supply-Focal	Supply-Cross	Demand-Cross	Demand-Cross
Context	Disruption	Violation	Disruption	Disruption	Violation

Note. Each risk type's acronym indicates the characteristics of its decision setting, with the first letter reflecting its structure and the second its context. Structure: S = Supply-Focal; C = Supply-Cross; R = Demand-Cross. Context: D = Disruption; V = Violation.

A safety violation (SV) occurs when a supplier does not comply with government-established safety protocols. If such a violation occurs and is detected during a safety audit, production will need to be shut down to carry out remedial activities, resulting in a reduction in supply quantity from that supplier. Note that this risk type also involves violations of business practices similar to RV, but its structure is similar to SD: the influence manifests on the supply side and is focal to the low-cost supplier. Since SD and SV share the same structure, the buyer's optimal sourcing strategy is the same under SD and SV, as shown in Figure 4.1(a).

A reputation disruption (RD) arises when a supplier's negative quality reputation harms customers' perception of the product the buyer sells. The following is an example of such as scenario: suppose the low-cost supplier also manufactures other products of lower quality in addition to the product sourced by the buying firm, and there is a possibility of a quality issue occurring with one of the other products. If such an issue occurs and the news becomes public, it could, by association, harm customers' perceptions of the buying firm, resulting in reduced customer demand, regardless of the product source. Notice that RD involves a process disruption similar to SD but carries the same risk structure as RV in that the impact shows up on the demand side and crosses over to both suppliers. Since RV and RD share the same structure, the buyer's optimal sourcing strategy is the same under RV and RD, as illustrated in Figure 4.1(c).



(a) Safety Violation (SV)

(b) Contamination Disruption (CD)

(c) Reputation Disruption (RD)

Figure 4.1: Buyer's Optimal Sourcing Strategy under Three Additional Risk Types

Finally, contamination disruption (CD) refers to cases in which products sourced from a supplier may lead to contamination incidents, reducing the total quantity of products available for sale. For example, sourcing from a low-cost supplier that has unreliable shipping and handling processes might result in product contamination, which can further contaminate the buyer's warehouse. If such a contamination occurs, a fraction of all products, regardless of the supplier, will not be suitable to sell to customers. Note that this risk structure provides an ideal middle point of comparison between the risk structures associated with SD and RD (i.e., supply-focal and demand-cross) because the influence domain is the supply side, similar to SD, but its cross-supplier scope is similar to RD.[1]

Since this additional risk type presents a novel structure that is not seen in SD or RV, we first establish a normative benchmark, as we did for SD and RV. Figure 4.1(b) illustrates how the buyer's optimal sourcing strategy varies based on the likelihood (δ_{CD}) and impact (γ_{CD}) of a contamination disruption (a detailed analysis can be found in the Appendix). Comparing across subfigures in Figure 4.1, we have a clearer view of how different structures influence the buyer's optimal sourcing strategy. As we see, when the impact is lower than a certain threshold ($\gamma_{CD} \leqslant \frac{c_\Delta}{c_H}$), the optimal sourcing strategy under supply-cross structure is similar to that under supply-focal structure. Specifically, supplier L remains the dominant choice, while the optimal order quantity varies according to the likelihood level. On the other hand, when the impact is high ($\gamma_{CD} > \frac{c_\Delta}{c_H}$), the optimal sourcing strategy under supply-cross structure resembles that under demand-cross structure. The optimal order quantity always equals d, but the optimal supplier to source from varies with the likelihood level.

Before concluding our discussion of the additional treatments, we note that SD, SV, RD, and RV constitute a parsimonious 2 (Structure: supply-focal vs. demand-cross) by 2 (Context: disruption vs. violation) factorial design to disentangle the effects of structural and contextual characteristics. In addition, SD-CD-RD forms a pivot design to isolate the influence of the two dimensions of structure (i.e., domain and scope).

We sought to recruit at least 100 participants for each treatment. In total, 531 participants (57.1% male; $M_{age} = 43.4$) completed all of the required activities (their assignment to each treatment is shown in Table 4.1). The final payment consisted of a flat participation fee of \$3.25 and a bonus payment based on the average profit across

[1] Besides parsimony considerations, we did not adopt a full-factorial design to include the demand-focal combination because we believe it is less realistic in practice. Even when provided with tracing technologies, customers may still be skeptical about the available information or even be infuriated by the firm's double standards. As a result, such damage control tactics may increase mistrust and perceived insincerity, which will sabotage the firm's overall business.

all rounds of the game, with a conversion rate of \$900 in the game = \$1 bonus. The average participant payment was \$7.12.

4.3 Comparison between Supply Disruption and Responsibility Violation Risks

In this section, we focus on the two main treatments corresponding to SD and RV to test the robustness of our results with the new participant pool. In the next section, we report on the three additional treatments designed to explore the underlying driving forces. Before analyzing the data, we remove data points corresponding to participants who exhibited the following outlier behaviors in at least one round: (1) set both Q_L and Q_H to zero (i.e., $Q = 0$), or (2) set $Q > 1665$, which is more than five times the highest possible optimal order quantity.[2] Two participants met this exclusion criterion, reducing the number of participants in the SD treatment from 102 to 100.

4.3.1 Diversification Behavior

We start by computing the proportion of buyers who diversify under each decision scenario. Figure 4.2 reports the corresponding 95% confidence intervals, with the averages ranging from 10% to nearly 80%. Similar to the pattern we observe in Study 1, the propensity to diversify appears to be lower under RV when compared with SD.

We still utilize logistic regressions to test Hypothesis 3.1, with the dependent variable $Diversification$ capturing whether or not the buyer diversifies. Our primary independent variable of interest, $RiskType$, is coded as 1 for the RV treatment and 0 otherwise. Table 4.2 reports the results. In Model 1 (i.e., Column "Diversification All"), the coefficient of $RiskType$ is negative and significant ($p < 0.001$), with the odds of diversification decreasing by $1 - e^{-1.825} = 83.88\%$ under RV. The corresponding average marginal effect is a 40.6 percentage point reduction in the probability of diversification under RV relative to SD. This result supports Hypothesis 3.1.

[2]Our conclusions do not change when using a higher threshold of $Q > 3300$, which is more than 10 times the highest possible optimal order quantity, to determine outliers.

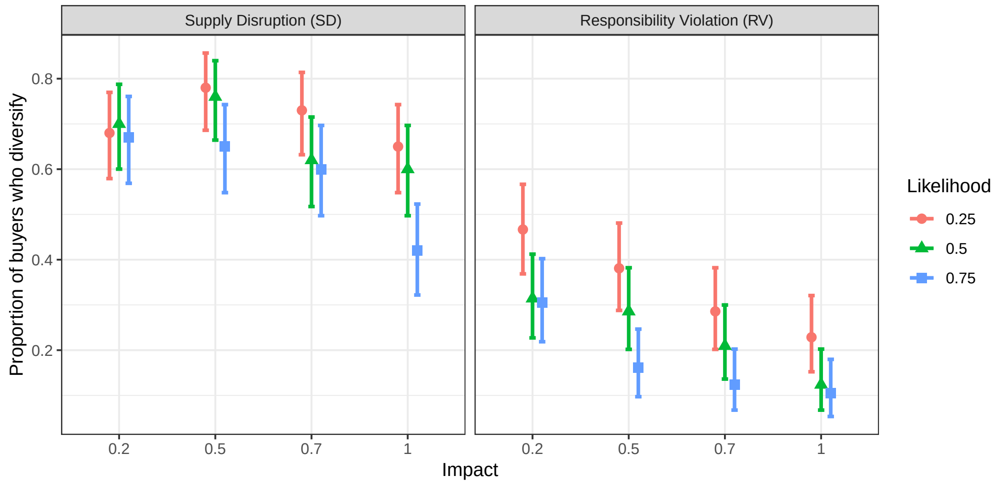


Figure 4.2: 95% Confidence Intervals of the Proportion of Buyers Who Diversify

4.3.2 Buyer Preference: Low- vs. High-cost Supplier

We continue to examine how buyers allocate orders across the two suppliers. Figure 4.3 displays a set of histograms of the proportion of orders awarded to supplier H under the two risk types. The top panel corresponds to scenarios in which supplier H is the profit-maximizing choice. A KolmogorovSmirnov test shows that the distributions of Q_H/Q under the two risk types are different ($p < 0.001$), with significantly less diversification under RV (logit regression, $p < 0.001$). Furthermore, the percentage of instances in which buyers choose to sole-source from supplier H (i.e., align with the optimal policy) appears to be substantially different under the two risk types, with around 40% under SD and nearly 80% under RV. To test the influence of risk type on buyers' sourcing strategies, we perform a set of logistic regressions on the likelihood of correct sole-sourcing. The results are reported in Table 4.2. Model 2 indicates that buyers' sourcing strategies are significantly different across the two risk types ($p < 0.001$), with the odds of sourcing exclusively from supplier H higher by $e^{1.922} - 1 = 583\%$ under RV. The corresponding average marginal effect represents a 41.1 percentage point increase in the probability of sole-sourcing from H (i.e., aligning with the optimal policy) under RV when compared with SD. This result provides support for Hypothesis 3.2.

Table 4.2: Logistic Regression Results on Diversification and Correct Sole-sourcing

	Diversification	Correct Sole-sourcing	
	All	OptSupplier = H	OptSupplier = L
	(1)	(2)	(3)
Constant	1.867***	-2.418***	-0.657
	(0.436)	(0.625)	(0.557)
Round	-0.012	0.043*	0.016
	(0.009)	(0.019)	(0.022)
Male	-0.103	-0.151	0.894**
	(0.233)	(0.276)	(0.283)
Age	-0.008	0.010	-0.017
	(0.009)	(0.010)	(0.012)
Impact 0.5	-0.108		-1.150***
	(0.103)		(0.179)
Impact 0.7	-0.481***	0.445**	-1.634***
	(0.111)	(0.162)	(0.248)
Impact 1	-0.862***	0.785***	-1.598***
	(0.121)	(0.162)	(0.303)
Likelihood 0.5	-0.372***	0.640**	-0.472***
	(0.081)	(0.210)	(0.119)
Likelihood 0.75	-0.738***	1.226***	-0.829***
	(0.103)	(0.238)	(0.160)
RiskType	-1.817***	1.935***	0.093
	(0.235)	(0.287)	(0.279)
Observations	2,460	1,035	1,425
Log Likelihood	-1428	-564.8	-566.1
Akaike Inf. Crit.	2876	1148	1152
Note:	+: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$		

The bottom panel of Figure 4.3 illustrates the scenarios in which supplier L is the profit-maximizing choice. From the figure, we see that buyers sole-source from supplier L roughly 20% of the time, and this proportion is comparable across the two risk types. Model 3 in Table 4.2 confirms that the probability of sole-sourcing from supplier L (i.e., aligning with the optimal policy) is indeed similar across the two risk types, as the coefficient of $RiskType$ is not statistically different from 0. This implies that neither

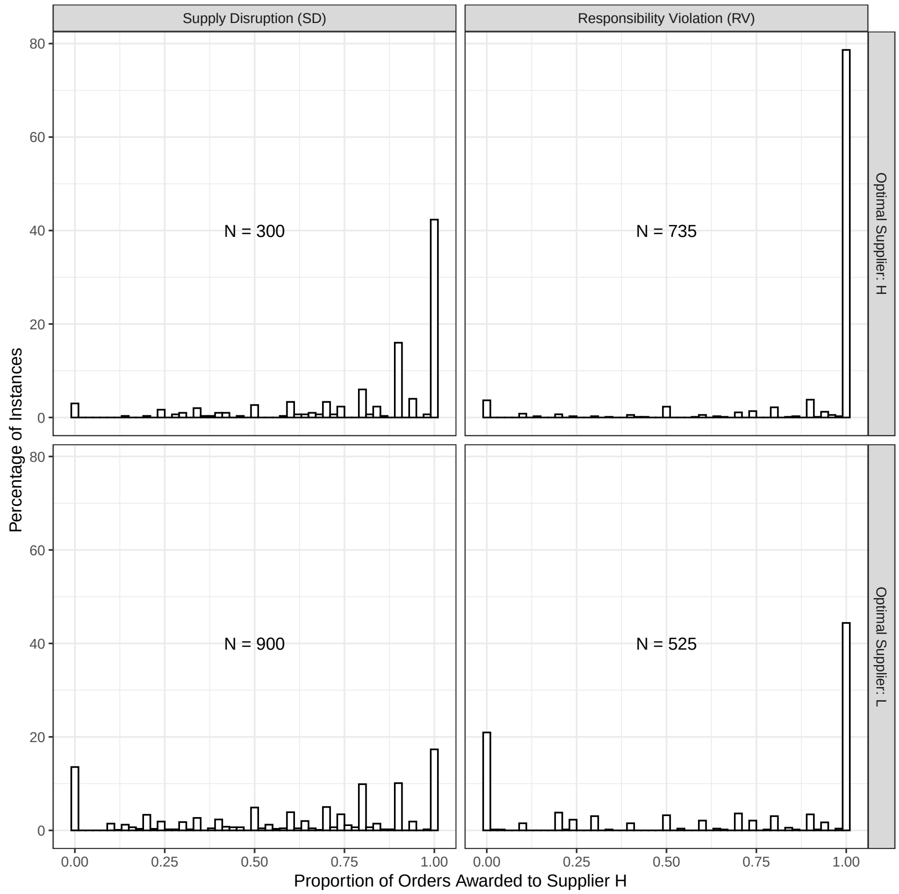


Figure 4.3: Histograms of the Proportion of Orders Awarded to Supplier H (Q_H/Q)

Hypothesis 3.3A nor Hypothesis 3.3B is supported. Note that this result is not driven by similarities in the level of diversification across the two risk types, since there is less diversification under RV (logit regression, $p < 0.001$). Instead, it appears that buyers who choose to not diversify under RV gravitate toward the high-cost supplier. As a result, we do not see significant differences across the two risk types with respect to participants' propensity to sole-source from the low-cost supplier. Overall, the results of this subsection suggest that there is lower diversification under RV and, furthermore, participants who choose not to diversify gravitate toward the high-cost supplier.

4.3.3 Influence of the Operating Environment

Hypothesis 3.4 predicted that buyers would respond to changes in likelihood by incrementally adjusting order allocation between the two suppliers instead of making step-wise changes, as the normative solution suggests. Figure 4.4 illustrates how buyers adjust the proportion of orders awarded to supplier H (i.e., Q_H/Q) as a function of likelihood under different impact levels and risk types. From the figure, we see that Q_H/Q increases monotonically with likelihood, following either a linear or a concave trend. These general trends are consistent across the two risk types, and more importantly, there is no evidence of the step-wise changes predicted by our normative models.

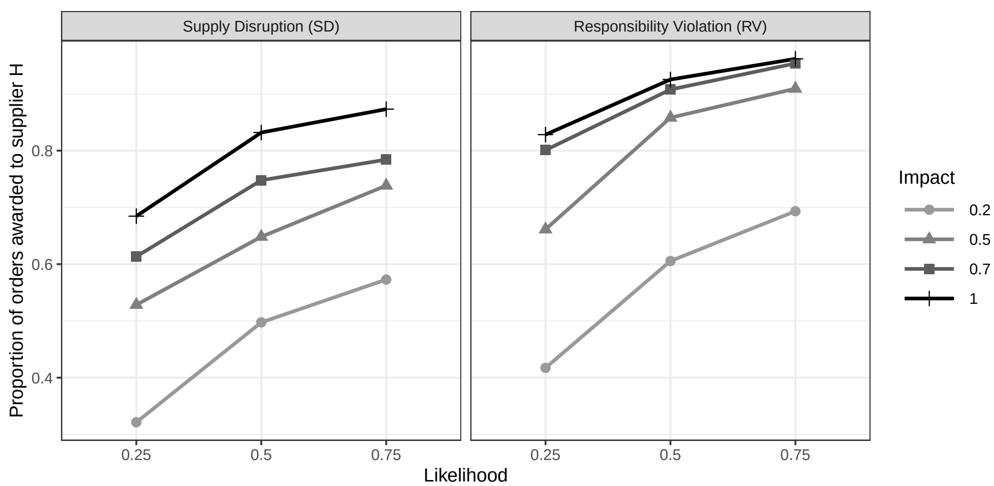


Figure 4.4: Proportion of Orders Awarded to Supplier H (Q_H/Q)

To formally test our hypothesis regarding buyers' behavior, we use OLS (ordinary least squares) regression models, with Q_H/Q as the dependent variable. Table 4.3 summarizes the results. As we see from Models 3 and 6, when likelihood increases from 0.25 to 0.5, the proportion of orders awarded to supplier H increases by 15 percentage points, with an additional increase of 5 percentage points as likelihood increases further from 0.5 to 0.75. This general pattern also holds when we examine the subsamples corresponding to low and high impact levels in Models 1-2 and 4-5. These results support Hypothesis 3.4.

Table 4.3: OLS Regression Results on the Proportion of Orders Awarded to Supplier H for Different Impact Levels (SD and RV)

	Supply Disruption (SD)			Responsibility Violation (RV)		
	Low-impact (1)	High-impact (2)	All (3)	Low-impact (4)	High-impact (5)	All (6)
Constant	0.442***	0.661***	0.360***	0.493***	0.755***	0.472***
	(0.024)	(0.021)	(0.028)	(0.045)	(0.020)	(0.031)
Round	-0.002	-0.002	-0.002	-0.011+	0.001	-0.003
	(0.003)	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)
Impact 0.5			0.174***			0.236***
			(0.029)			(0.032)
Impact 0.7			0.251***			0.315***
			(0.034)			(0.033)
Impact 1			0.332***			0.331***
			(0.032)			(0.033)
Likelihood 0.5	0.147***	0.140***	0.144***	0.188***	0.134***	0.147***
	(0.020)	(0.028)	(0.019)	(0.036)	(0.024)	(0.022)
Likelihood 0.75	0.230***	0.179***	0.205***	0.276***	0.178***	0.203***
	(0.025)	(0.026)	(0.022)	(0.041)	(0.026)	(0.025)
Participant FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	600	600	1200	315	945	1260
R-squared	0.133	0.132	0.287	0.230	0.135	0.300
Adjusted R-squared	0.128	0.128	0.283	0.223	0.132	0.297

Note: +: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

4.4 Disentangling Structure and Context

In this section, we utilize data from all five treatments to revisit our behavioral theories that support Hypotheses 3.1 through 3.3. If our behavioral theories hold, we should expect buyers' ordering patterns to be consistent with the directional predictions from our hypotheses. Before analyzing the data, we applied the same exclusion criteria as in section 4.3, reducing the sample size to 112 for the SV treatment, 102 for the RD treatment, and 107 for the CD treatment.

4.4.1 Assessing the Effect of Structure

We first examine the effect of structure (i.e., domain and scope) on buyers' ordering behavior. Specifically, we compare buyers' ordering decisions across supply-focal vs. demand-cross structures while holding the context fixed (either violation or disruption). If structure is an important driver, we would expect buyers facing the demand-cross structure to diversify less frequently and correctly sole-source more often, as the arguments leading up to our hypotheses predict. When the risks involve violations (i.e., SV-RV comparison), buyers diversify less and are more likely to correctly sole-source when the optimal supplier is H (ps$<$ 0.05) under RV relative to SV. In scenarios in which the optimal supplier is L, we do not detect any difference in correct sole-sourcing between RV and SV ($p > 0.1$), but the distributions of Q_H/Q are significantly different (KolmogorovSmirnov test, $p < 0.001$). We observe a similar pattern when comparing the risks that involve disruptions (i.e., SD-RD comparison). Therefore, these two sets of comparisons produce consistent results as in the SD-RV comparison in section 4.3, upholding H3.1 and H3.2 but neither H3.3A nor H3.3B.

While general support for H3.1 and H3.2 is expected, the universal rejection of H3.3A and H3.3B is not. Recall that in our hypothesis development, the pair of competing hypotheses regarding buyers' correct sole-sourcing behavior when the optimal supplier is L (i.e., H3.3A and H3.3B) resulted from incongruent forces of cognitive processing and affective reactions that point in opposite directions under such scenarios. When comparing SV and RV in Study 2, we expect to observe and indeed find the same result for H3.3A and H3.3B as in the prior SD-RV comparison, since the incongruence between cognitive processing and affective reactions is still present. However, this should not be the case when comparing SD and RD. Since these two risk types do not involve violations, the potential influence of affective responses is minimized. As a result, we should expect the effect of cognitive processing to dominate and H3.3A to hold in the SD-RD comparison (i.e., more correct sole-sourcing under the demand-cross structure vs. supply-focal structure). However, our finding is unexpectedly consistent with the prior SD-RV comparison. Taken together, these results suggest that our behavioral theories regarding the influence of structure largely hold true, and that a considerable portion of the differences between SD and RV can be attributed to their different structures. Nevertheless, buyers face unique challenges when the optimal supplier is L. In this case, even when the influence of affective reactions is supposed to be limited (as in the SD-RD comparison), it appears that buyers are not able to overcome their aversion to sourcing entirely from supplier L. This aversion could negate the benefits of cognitive processing that might point in the direction of supplier L, resulting in no significant differences in sourcing behavior between the two risk types when the optimal supplier is L.

With the help of the novel risk structure introduced by CD, we can further assess the relative influence of the domain and scope dimensions parsimoniously through the SD-CD-RD comparison. The SD-CD comparison helps isolate the effect of scope, while the CD-RD comparison helps isolate the influence of domain. If we observe greater differences in the SD-CD comparison but less in the CD-RD comparison (or vice versa), then we can credit more weight to one dimension vs. the other with respect to the relative influence over buyers' sourcing strategies.

When comparing SD vs. CD, we observe that participants under CD diversify less ($p < 0.001$) and are more likely to sole-source from the optimal supplier when the optimal option is H ($p < 0.001$). When the optimal option is L, there is no significant difference in correct sole-sourcing ($p > 0.1$), but the distributions of Q_H/Q are different (KolmogorovSmirnov test, $p < 0.001$). These results resemble the pattern we previously observed when examining the differences between SD and RD. In comparing CD vs. RD, we find that participants under the two risk types have different levels of diversification, with buyers under RD diversifying more ($p = 0.041$). There is no significant difference with regard to correct sole-sourcing in either of the two subsamples with different optimal supplier scenarios (ps > 0.1). In addition, KolmogorovSmirnov tests on these two subsamples reveal that the distributions of Q_H/Q under the two risk types only differ from each other with borderline statistical significance ($p = 0.049$ when L is optimal; $p = 0.066$ when H is optimal). Therefore, when examining the influence of the structure, it appears that the scope dimension plays a more important role than the domain dimension in determining buyers' overall sourcing behavior.

4.4.2 Assessing the Effect of Context

We now turn our attention to the effect of context—the other critical characteristic that differentiates SD and RV. Specifically, we compare buyers' ordering decisions across risk types involving different contexts, i.e., when the risk involves a disruption vs. a violation, under the same risk structure (either supply-focal or demand-cross). If context matters, then we would expect that buyers making sourcing decisions in settings involving the prospect of a violation (vs. a disruption) to diversify less and more likely to sole-source from H.

Starting with the RD-RV comparison, we find that participants under RV exhibit significantly less diversification behavior ($p = 0.0336$) than those under RD. But there is no difference across the two risk types with respect to correct sole-sourcing (ps> 0.1). The distributions of Q_H/Q are significantly different when the optimal supplier is L (KolmogorovSmirnov test, $p = 0.034$), a situation that creates tension between cognitive processing and affective reactions, but not when the optimal supplier is H ($p > 0.1$). On the other hand, in the SD-SV comparison, we do not observe any significant difference concerning the main dependent variables (diversification and correct sole-sourcing for the two subsamples with different optimal suppliers, ps> 0.1), and the distributions of Q_H/Q are only marginally significantly different (KolmogorovSmirnov tests, $0.05 < p$s < 0.1). Because it is only under the demand-cross structure that we observe significant differences in buyers' diversification behavior and detect significant differences in Q_H/Q distributions, it appears that the influence of context is more salient when the impact manifests on the demand side and crosses over to the high-cost supplier. This may be attributable to the fact that customer boycotts and high stakes magnify the salience of emotional responses.

4.4.3 Assessing the Robustness of Order Allocation Adjustment Behavior

When comparing buyers' sourcing behaviors under SD and RV in Study 1, we observe not only prominent differences in ordering patterns, but also notable similarities in order allocations when likelihood levels change. Specifically, we find that buyers allocate more orders to the high-cost supplier in an incremental way whenever the likelihood increases, providing evidence to support H3.4. In this section, we examine the robustness of this result using the three additional treatments introduced in Study 2. Table 4.4 summarizes the OLS regression results on Q_H/Q. As we see, regardless of the structure and context combinations, buyers award more orders to H when the likelihood is higher. Therefore, the incremental manner in which buyers adjust order allocations as the likelihood changes is robust across different risk types.

To summarize the findings from this section, we see that structure and context characteristics both contribute to buyers' different sourcing behaviors across SD vs. RV, but their relative significance varies. In terms of diversification, both dimensions of structure characteristics (i.e., domain and scope) matter, regardless of context. Buyers

Table 4.4: OLS Regression Results on the Proportion of Orders Awarded to Supplier H for Different Impact Levels (SV, CD, and RD)

	Safety Violation (SV)			Contamination Disruption (CD)			Reputation Disruption (RD)		
	Low-impact (1)	High-impact (2)	All (3)	Low-impact (4)	High-impact (5)	All (6)	Low-impact (7)	High-impact (8)	All (9)
Constant	0.495***	0.677***	0.384***	0.507***	0.805***	0.534***	0.494***	0.750***	0.472***
	(0.021)	(0.021)	(0.026)	(0.041)	(0.018)	(0.027)	(0.031)	(0.020)	(0.032)
Round	-0.006*	-0.003	-0.003	-0.009+	-0.004+	-0.006**	-0.006	0.002	0.002
	(0.003)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Impact = 0.5			0.171***			0.242***			0.219***
			(0.023)			(0.032)			(0.029)
Impact = 0.7			0.260***			0.273***			0.278***
			(0.028)			(0.034)			(0.033)
Impact = 1			0.338***			0.300***			0.312***
			(0.032)			(0.034)			(0.034)
Likelihood = 0.5	0.152***	0.180***	0.167***	0.207***	0.137***	0.155***	0.159***	0.125***	0.135***
	(0.021)	(0.023)	(0.017)	(0.035)	(0.023)	(0.021)	(0.028)	(0.019)	(0.017)
Likelihood = 0.75	0.214***	0.225***	0.220***	0.281***	0.172***	0.200***	0.263***	0.173***	0.196***
	(0.025)	(0.024)	(0.021)	(0.038)	(0.024)	(0.022)	(0.036)	(0.023)	(0.022)
Participant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	672	672	1344	321	963	1284	306	918	1224
R-squared	0.145	0.219	0.333	0.248	0.135	0.270	0.284	0.135	0.298
Adjusted R-squared	0.141	0.215	0.330	0.241	0.133	0.267	0.277	0.133	0.295

Note: +: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

are less likely to diversify when the risk event influences the demand side of the supply chain or when it influences both H and L (vs. only L). In contrast, context only matters under the demand-cross structure. In such cases, buyers diversify less when the risk involves a violation (vs. a disruption). In terms of correct sole-sourcing, only the scope dimension matters. When the impact is pervasive and influences both suppliers, buyers are more likely to correctly sole-source when the optimal supplier is H. None of the structure and context characteristics appear to significantly influence correct sole-sourcing when the optimal supplier is L. Therefore, structure, especially the scope of the risky event's impact, primarily explains the differences we observe between SD and RV, while context plays a less critical role.

4.5 Performance Implications

After comparing buyers' sourcing behaviors under SD vs. RV and disentangling the effect of the structural and contextual characteristics, we move one step further to evaluate the performance implications of buyers' sourcing strategies. This evaluation not only helps generate valuable managerial insights to guide sourcing decisions under

SD and RV, but also brings to light some potential improvement programs generalizable to other risk types with comparable characteristics. Our analysis within each risk type focuses on how buyers' sourcing strategies influence their Expected Profit Ratio (EPR), an efficiency measure defined as the actual expected profit divided by the optimal expected profit in each round, i.e., $EPR = \pi_i(Q_L, Q_H)/\pi_i(Q_L^*, Q_H^*)$. A higher EPR indicates better performance.

Figure 4.5 exhibits buyers' average EPR across different likelihood and impact levels under each of the five risk types. We see that the influence of risk structure and context on buyers' sourcing decisions, as highlighted in section 4.4, is also evident in the EPR. Across the three types of risk structures, it is clear that the SD-SV group has similar increasing trends as the impact rises, exhibiting great variation across different scenarios. The patterns of the RD-RV group, on the other hand, are relatively stable in a confined band. CD is somewhere in between, such that there is considerable variation in the low-impact region but not in the high-impact region. Context seems to matter too, but only in the RD-RV group. Specifically, RV exhibits a higher EPR level relative to RD across different scenarios. In addition to the two observations that echo our prior findings, we also notice that buyers under SD and RV exhibit different performances as impact levels vary. In the low-impact region, buyers under RV perform better, while in the high-impact region, buyers under SD perform better.

Although these patterns display buyers' *average* performances across different scenarios, we do not yet know how buyers' performances vary according to their sourcing decisions. Only through a better understanding of the performance implications of different sourcing strategies *within* each risk type can we provide actionable insights to guide buyers' decisions under a specific risk. Therefore, based on our behavioral findings for SD and RV, we investigate how diversification and a preference for the high-cost supplier may influence buyers' EPR, and what individual characteristics may be associated with the adoption of these strategies.

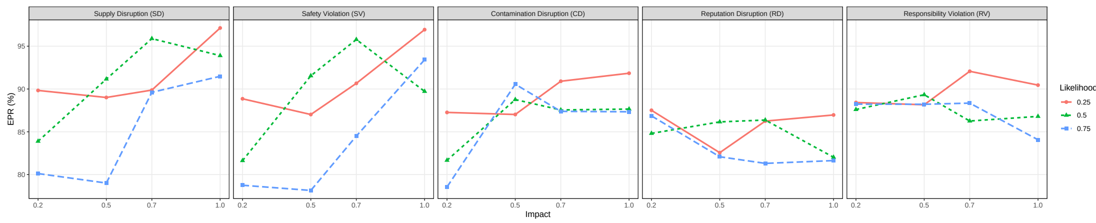


Figure 4.5: Average EPR across Different Risk Types

4.5.1 How Much Does Diversification Bias Cost?

Although our normative models demonstrate that sole-sourcing is optimal regardless of the risk type, we observe considerable heterogeneity in buyers' tendency to diversify in our behavioral experiments. Hence, we seek to understand how much diversification bias costs buyers, and whether overcoming such bias would help to improve their performance.

We utilize a set of OLS regressions on EPR to investigate this question. In our regression models, the independent variable of interest is $Diversification$, a binary variable indicating whether or not a buyer diversifies in one round, which we used as the dependent variable to test H3.1 in section 4.3. The regression results are summarized in Table 4.5. As we see, diversification negatively influences performance under both SD and RV, and the detrimental effect is more prominent under RV, where diversification decreases EPR by 36.1 percentage points, on average.

Given that diversification negatively influences performance, we are interested in obtaining a sense of the persistency of buyers' strategies, specifically in terms of how consistently buyers diversify or sole-source across the 12 rounds. We classify buyers into three general groups: Diversifier (who always dual-sources), SoleSourcer (who always sole-sources), and Explorer (who engages in both dual-sourcing and sole-sourcing). Table 4.6 lists the breakdown of each group under SD and RV. As we see, the proportion of Explorers is very similar across the two risk types. What differentiates the two risk types is the relative composition of the other two groups—there are significantly fewer Diversifiers under RV (less than 6%) compared with SD (more than 30%). Our results in section 4.3 indicate that buyers under RV diversify less on average, supporting H3.1. This new analysis provides additional evidence that this behavior also manifests in the

Table 4.5: Influence of Diversification on EPR

	SD	RV
	(1)	(2)
Constant	0.907***	1.039***
	(0.014)	(0.025)
Round	0.001	0.003**
	(0.001)	(0.001)
Impact 0.5	0.021**	-0.024*
	(0.007)	(0.012)
Impact 0.7	0.070***	-0.048**
	(0.007)	(0.017)
Impact 1	0.088***	-0.083**
	(0.010)	(0.027)
Likelihood 0.5	-0.005	-0.061***
	(0.007)	(0.013)
Likelihood 0.75	-0.072***	-0.087***
	(0.008)	(0.019)
Diversification	-0.065***	-0.361***
	(0.009)	(0.028)
Observations	1,200	1,260
R^2	0.250	0.451
Adjusted R^2	0.245	0.448
Note:	+: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$	

persistency of buyers' sourcing strategies such that very few buyers always diversify under RV, while many do so under SD.

Table 4.6: Consistency of Sourcing Strategy (Diversification vs. Sole-sourcing)

Risk Type	Diversifier	Explorer	SoleSourcer
SD	30.7	57.4	11.9
RV	5.7	51.4	42.9

4.5.2 How Much Does Favoring the High-cost Supplier Cost?

Our analysis clearly shows that diversification hurts performance and that buyers should consider sole-sourcing to improve EPR. The next natural question is how to choose between the two options of sole-sourcing from H vs. L. When we examined buyers' preference for these two supplier candidates in our behavioral experiments, one striking finding was that participants gravitated toward H more often, even in scenarios when it was optimal to sole-source from L. Given buyers' tendency to favor H, we seek to examine the performance implication of sole-sourcing from H across scenarios with different optimal suppliers.

Similar to the previous subsection, we utilize a set of OLS regressions to investigate how different sourcing strategies influence EPR. In our regression models, diversification is the omitted reference group, and we further divide sole-sourcing into two categories: H sole-sourcing (H-$Sole = 1$) and L sole-sourcing (L-$Sole = 1$). The results are summarized in Table 4.7 by different optimal supplier scenarios. Under RV, H sole-sourcing is always better than diversification. When H is the optimal supplier (Model 2), this improvement is substantial (64.7 percentage points); even when L is the optimal supplier (Model 4), H sole-sourcing still improves EPR by nearly 9 percentage points relative to diversification. Under SD, H sole-sourcing leads to strong performance outcomes compared with diversification. It improves EPR when H is the optimal supplier (Model 1) and achieves similar EPR when L is the optimal supplier (Model 3). In comparison, L sole-sourcing is not as robust, since it reduces EPR under SD when the optimal supplier is H.

Notice that in addition to predicting robust performance improvements over diversification, H sole-sourcing has special implications for RV, since it helps achieve win-win outcomes that benefit the buying firm as well as society. When examining the consistency of SoleSourcers' strategies, we find that participants indeed avoid exclusively doing business with L, as no one consistently sole-sourced from L. But the benefit of committing entirely to H appears to not be fully recognized by the majority of the SoleSourcers, as the proportions of SoleSourcers who always source from H are both below 50% under SD and RV, although this proportion is higher under RV when compared with SD (38.86% vs. 16.81%).

Table 4.7: Influence of Different Sole-sourcing Strategies on EPR

	OptSupplier = H		OptSupplier = L	
	SD	RV	SD	RV
	(1)	(2)	(3)	(4)
Constant	0.928***	0.533***	0.830***	0.790***
	(0.013)	(0.041)	(0.014)	(0.013)
Round	0.001	0.001	0.001	0.002+
	(0.001)	(0.002)	(0.001)	(0.001)
Impact 0.5			0.033***	0.011
			(0.006)	(0.012)
Impact 0.7		-0.060***	0.079***	0.049***
		(0.011)	(0.008)	(0.013)
Impact 1	-0.036***	-0.110***	0.122***	
	(0.010)	(0.022)	(0.012)	
Likelihood 0.5		-0.109***	0.005	-0.015
		(0.023)	(0.009)	(0.011)
Likelihood 0.75	-0.036**	-0.169***	-0.058***	-0.0001
	(0.014)	(0.031)	(0.009)	(0.013)
H-Sole	0.106***	0.647***	0.010	0.088***
	(0.010)	(0.030)	(0.013)	(0.009)
L-Sole	-0.242***	0.262***	0.115***	0.193***
	(0.071)	(0.058)	(0.010)	(0.009)
Observations	300	735	900	525
R^2	0.411	0.761	0.302	0.477
Adjusted R^2	0.401	0.759	0.295	0.470
Note:	+: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$			

4.5.3 What Individual Attributes Are Associated with Diversification and Favoring the High-cost Supplier?

As our analysis highlights the finding that diversification is detrimental while H sole-sourcing is beneficial, it is crucial to understand whether certain individual attributes contribute to buyers' adoption of these strategies. By uncovering the link between individual differences and strategy adoption, we open new opportunities to nudge buyers toward improved decision quality. Guided by our behavioral theories in section 3.3, we focus on cognitive and affective aspects to identify potential influencing factors.

Our behavioral theories suggest that cognitive processing and affective reactions influence buyers' decisions in different ways. On the cognitive side, a complex risk structure requires buyers to adopt a different mindset. When the impact of a risky event crosses over to the high-cost supplier, buyers must understand the "all-or-nothing" nature of risk exposure in order to make informed decisions. Buyers who understand this unique risk structure are more likely to prioritize sole-sourcing strategies. However, prior literature points out that it is common for people to adopt linear heuristics when making decisions. Buyers who are under the influence of this bias may perceive the overall supply chain risk exposure to be linear in terms of the order quantity from the low-cost supplier and will find it more challenging to handle this risk structure. Therefore, buyers' tendency to engage in linear thinking might negatively correlate with their likelihood of adopting sole-sourcing strategies when the risk scope extends beyond the focal supplier. On the other hand, although this understanding helps reduce diversification, it does not necessarily improve the chances of committing to H, because buyers can lower costs while accepting a certain level of risk by sole-sourcing from L. To capture this difference in participants' tendency to engage in linear thinking in terms of risk exposure, we adopt a scenario question specific to each risk type as part of the survey questions (see Appendix). The variable $LinearThinking$ takes the value of 1 if a participant perceives the overall risk exposure to increase when order quantities from the low-cost supplier increase, and 0 otherwise.

On the affective side, an emotion-laden context can shift buyers' preferences between the two suppliers. When the risk involves a business practice violation, strong reactions should push buyers away from doing business with the low-cost supplier, which engages in potentially questionable practices, and toward the high-cost supplier. In other words, strong affective reactions not only reduce diversification but also increase the likelihood of committing to sole-sourcing from H. To capture differences in buyers' affective reactions, we measure their perception of the low-cost supplier's control and responsibility for the risky event, which is assessed using a seven-point Likert scale. Following Tang et al. (2020), we asked participants in the survey to rate the extent to which they think the low-cost supplier had "control" and "influence" over the outcome and was "responsible," "accountable," and "blameworthy" for the risky event on a 1 (*not at all*) to 7 (*extremely*) scale. The five items show high reliability ($\alpha = 0.88$) and thus their mean is used for the $ControlResponsibility$ measure.

We added three control variables in our analysis. The first two are participants' gender and age. To control for the general cognitive capability that has been shown to influence decision-making (e.g., Moritz et al. 2013), we include the third control variable to capture participants' cognitive reflection level using the established cognitive reflection test (Frederick 2005). Following prior studies in behavioral operations management (e.g., Csermely and Minner 2015, Narayanan and Moritz 2015), we classify participants with at least two correct answers in cognitive reflection test as the High CR group ($CRHigh = 1$) and the rest as the Low CR group ($CRHigh = 0$).

We include the above-referenced individual attributes as independent variables in a series of logit regressions, with the dependent variable being the strategy used in each round. Table 4.8 summarizes the relationship between individual attributes and the tendency to diversify. As we see, $LinearThinking$ increases the likelihood of diversification under RV but has no effect under SD. On the other hand, $ControlResponsibility$ reduces buyers' likelihood of using a diversification strategy under RV but has no effect under SD. These results are consistent with our theory. $LinearThinking$ increases diversification only when the scope is broad and affective reactions can reduce diversification when the context involves violations.

Employing a similar format, Table 4.9 summarizes the relationship between individual attributes and the tendency to sole-source from H. In these two models, $LinearThinking$ has no significant influence under either SD or RV. However, we see that $ControlResponsibility$ significantly increases the likelihood of sole-sourcing from H. Again, these results support our theory that highlights the role of affective reactions in pushing buyers toward exclusively sourcing from the high-cost supplier, which does not involve any moral ambiguity. Taken together, these results confirm our behavioral theory regarding how cognitive and affective aspects influence buyers' sourcing decisions in different ways. While cognitive processing can narrow the choice set, it does not tilt buyers toward either the high- or low-cost supplier. In contrast, affective reactions nudge buyers toward the high-cost supplier, which in turn reduces diversification tendencies.

Table 4.8: The Relationship between Individual Attributes and Diversification

	SD	RV
	(1)	(2)
Constant	2.454***	2.418*
	(0.735)	(0.983)
Round	0.011	-0.044*
	(0.011)	(0.018)
Impact 0.5	0.234+	-0.503**
	(0.142)	(0.163)
Impact 0.7	-0.154	-0.929***
	(0.153)	(0.173)
Impact 1	-0.564***	-1.379***
	(0.141)	(0.226)
Likelihood 0.5	-0.193+	-0.636***
	(0.107)	(0.138)
Likelihood 0.75	-0.578***	-1.053***
	(0.128)	(0.192)
Age	-0.014	0.005
	(0.012)	(0.013)
Male	-0.139	-0.072
	(0.323)	(0.341)
CRHigh	-0.596+	-0.541
	(0.325)	(0.377)
LinearThinking	-0.256	0.904*
	(0.379)	(0.359)
ControlResponsibility	-0.062	-0.416***
	(0.121)	(0.097)
Observations	1,200	1,260
Log Likelihood	-735.614	-598.152
Akaike Inf. Crit.	1,495.229	1,220.304
Note:	+: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$	

Table 4.9: The Relationship between Individual Attributes and Sole-sourcing from H

	SD	RV
	(1)	(2)
Constant	-4.823***	-4.231***
	(0.847)	(1.039)
Round	-0.015	0.021
	(0.016)	(0.018)
Impact 0.5	0.909***	1.343***
	(0.266)	(0.192)
Impact 0.7	1.567***	1.936***
	(0.273)	(0.209)
Impact 1	2.146***	2.312***
	(0.277)	(0.240)
Likelihood 0.5	0.865***	0.895***
	(0.184)	(0.148)
Likelihood 0.75	1.400***	1.450***
	(0.197)	(0.196)
Age	0.018	0.015
	(0.012)	(0.013)
Male	-0.377	-0.205
	(0.326)	(0.311)
CRHigh	0.390	0.366
	(0.372)	(0.344)
LinearThinking	0.082	-0.418
	(0.383)	(0.308)
ControlResponsibility	0.168	0.359***
	(0.123)	(0.107)
Observations	1,200	1,260
Log Likelihood	-560.500	-656.629
Akaike Inf. Crit.	1,145.000	1,337.257

Note: +: $p < 0.1$; *: $p < 0.05$; **: $p < 0.01$; ***: $p < 0.001$

4.6 Discussion and Conclusions

This study continues our comparison between buyers' sourcing decisions under SD and RV in terms of the extent of diversification and the probability of selecting the optimal supplier. We first establish the robustness of these behavioral regularities with a different participant pool possessing management experience.

Our research then goes one step further to identify the exact source of the variation in buyers' sourcing behavior under SD and RV. Based on the risk taxonomy we propose, we introduce three additional treatments and systematically vary their structure and context characteristics. This design offers the opportunity to isolate the effects of structure and context characteristics, allowing us to compare the relative influence of these characteristics on our dependent variables of interest (i.e., diversification and correct sole-sourcing). Our analysis reveals that structure characteristics, particularly the scope of influence, are the dominant influencing factors, while context characteristics play a less important role. Specifically, participants tend to diversify less and are more likely to correctly sole-source when the high-cost supplier is optimal under a risk type that influences both suppliers in the supply base (i.e., scope = cross). In contrast, it appears that context only matters when the structure is demand-cross. Under such circumstances, participants facing a violation context tend to diversify less than those facing a disruption context. One interesting observation is that buyers seem to be averse to fully committing to the low-cost supplier when that supplier is the profit-maximizing option. Even when the context is neutralized, we still do not observe more correct sole-sourcing when the low-cost supplier is optimal. This question is left for future research.

We take advantage of the opportunities offered by our data to evaluate how buyers' behavioral decisions, as described above, translate into their profit performance. Our analysis reveals that buyers perform worse when they diversify (vs. sole-source). When they do recognize the need to sole-source, our analysis further demonstrates that it is better for buyers to err toward sole-sourcing from the high-cost supplier. Under SD, sole-sourcing from H improves performance compared with diversification when the optimal supplier is H, as we can expect, while its effectiveness is on par with a diversification strategy when the optimal supplier is L. Under RV, sole-sourcing from H is even better. It improves performance over diversification when the optimal supplier is H or L. There are two potential reasons behind this result. First, from the supplier selection perspective, committing to H helps overcome the more serious issue of diversification and prevent the loss due to diversification bias, as we witness in section 4.5.1. Second, from the order quantity decision perspective, committing to H helps avoid errors in order quantity adjustment: on the normative side, as shown in our analytical models, sourcing from L is associated with another decision problem of determining how much to order, whereas sourcing from H always implies ordering up to demand; on the behavioral side, order quantity adjustment proves to be a difficult task—our experimental results in Study 1 show that participants often neglect the need to make adjustments in order quantities, and even when they do adjust, they do not necessarily choose the correct direction. As a result, H sole-sourcing can serve as a fool-proof strategy to fend off other decision errors.

Because avoiding diversification and favoring the high-cost supplier are important in improving buyers' performance, it is helpful to understand who are naturally more inclined to pursue these strategies. These insights into the association between individual characteristics and strategy adoption provide potential avenues for nudging buyers. Consistent with our behavioral theories, our results demonstrate that cognitive processing and affective reactions influence buyers' ordering decisions through different channels. Cognitive factors, as exemplified by a linear thinking style, may influence buyers' propensity to identify sole-sourcing as a candidate solution but may not necessarily push them to exclusively sole-source from H. However, affective factors, such as perceived control and responsibility, influence buyers' tendency to sole-source primarily through encouraging more H sole-sourcing. Therefore, our results suggest that there are two potential ways to help buyers achieve better performance. First, helping buyers to understand the all-or-nothing nature of risk structure is critical when the scope is broad. This improves their tendency to consider a sole-sourcing strategy. Second, highlighting the potential social consequences of sourcing from suppliers with potential business practice problems or utilizing subconscious priming techniques aimed at improving ethical decision-making (e.g., Welsh and Ordóñez 2014) may induce the activation of affective reactions, which in turn encourages more sole-sourcing from the risk-free supplier.

Our study can be extended and expanded in the following directions. First, firms face increased scrutiny from governments for their supply chain conduct (e.g., Knolle and Evans 2021) and even legal challenges associated with their suppliers' business practices (e.g., Hurley 2021). It may be helpful to further explore other risk types arising from these additional stakeholder actions in future research. Second, these additional risk types may require a more complex risk taxonomy to disentangle their differences. Our risk taxonomy serves as a starting point for those future endeavors. Finally, our analysis examines the influence of selective cognitive and affective factors on buyers' sourcing strategies. Future studies may expand the selection of individual attributes and consider alternative measures to capture these factors. In addition, it may be valuable to explore potential interventions for behavioral changes by combining individual differences and situational characteristics (Figner and Weber 2011, p. 215).

Chapter 5

Study 3: Capacity Investment in Global Vaccine Supply Chains under Regulatory Risks

5.1 Introduction

The COVID-19 pandemic illustrates how global crises can create considerable pressure on healthcare supply chains. By June 2021, the pandemic had claimed more than 3.9 million lives and more than 182 million people had tested positive worldwide.[1] At earlier stages of the pandemic, countries focused significant effort on producing or procuring personal protection equipment (PPE) and other necessary medical supplies to contain infections and treat infected patients. To deal with supply shortages amid rapidly rising demand, governments resorted to a variety of political and administrative approaches to acquire critical medical supplies, often at the expense of other countries. It is reported that by June 2021, more than 100 trade-related policies restricting export control related to medical supplies are still active.[2]

As vaccines emerge as a key tool to combat the pandemic, some governments have

[1] Johns Hopkins University Center for Systems Science and Engineering. COVID-19 Data Repository. `https://github.com/CSSEGISandData/COVID-19`. See also Dong et al. (2020).

[2] World Bank. COVID-19 Trade Policy Database: Food and Medical Products. `https://www.worldbank.org/en/topic/trade/brief/coronavirus-covid-19-trade-policy-database-food-and-medical-products`.

used export restrictions specifically targeting this critical commodity as a reaction to public and political pressure to ensure sufficient domestic vaccine supply. This situation confirms prior concerns, raised as early as mid-2020, that governments' previous protection actions toward medical supplies like PPE would expand to vaccines once they became available (Loftus and Hinshaw 2020). A number of governments, including the European Union, the United States, and India, have enacted vaccine export controls in various forms (Vela and Heath 2021, Williams and Stacey 2021, Menon 2021), despite warnings from a variety of relevant communities on the dangers of "vaccine nationalism" (e.g., Weintraub et al. 2020, Kupferschmidt 2020).

Such government interventions to limit exports have important implications for firms' production capacity investment decisions, since they introduce regulatory risks to supply chains (Pournader et al. 2020) and present unique challenges to vaccine manufacturers with respect to managing their international production and distribution networks. More specifically, manufacturers may be confronted with the dilemma of either adding more capacity at an existing location in the home country where the manufacturer is based (referred to as the 'domestic' country in our analysis) or expanding production in a different country (referred to as 'overseas' country) to mitigate the effects of export restrictions from the domestic government. In the case of the COVID-19 vaccine, some manufacturers reportedly considered these capacity implications even before their candidate vaccines were approved due to strong concerns over potential vaccine nationalism issues (Loftus and Hinshaw 2020). When approaching the general question of whether to diversity production across multiple locations, manufacturers try to weigh the efficient benefits of pooling capacity with the potential localized cost benefits that diversification can offer (Schmitt et al. 2015, Kulkarni et al. 2004). The equation changes with the prospect of regulatory mandates that may restrict product movement between countries. However, there is little research available to guide vaccine manufacturers' decisions on whether to diversify and how much capacity to commit when facing challenges associated with this unique regulatory risk. On the other hand, without a good understanding of manufacturers' potential reactions to these regulatory mandates, governments cannot accurately assess how such mandates will play out and eventually impact vaccine availability and public health outcome. Therefore, a detailed analysis of the potential policy implications of such regulatory mandates is needed to inform policy decisions.

This study aims to address these gaps by examining the following research questions: (1) When faced with a regulatory mandate, how does a vaccine manufacturer change its capacity commitment strategy (i.e., pool all production in the domestic market vs. produce in both markets) and corresponding capacity levels? (2) How do these decisions change based on the type of regulatory mandate imposed? (3) What implications do these decisions have on key performance measures related to vaccine availability and public health outcome?

We address these questions by constructing a set of analytical models that capture the capacity investment decisions of a vaccine manufacturer considering two production locations in light of uncertain demand and potential regulatory mandates that restrict the export of vaccines. Profit margins may differ across the two countries based on differences in unit retail price, unit production cost, and transportation cost from the domestic to the overseas market. We start by examining how the manufacturer sets capacity levels for each country without regulatory intervention. Next, we investigate how the manufacturer's optimal decisions change when regulatory mandates are imposed by the domestic government to regulate vaccine export from the domestic country to the overseas country. We focus on two types of regulatory mandates: a random ban, where there is a probability that the government could ban export to the overseas country outright, and priority requirement, where the firm must ensure it meets all domestic demand before being allowed to export.

Our analytical models help characterize the manufacturer's optimal capacity commitment strategy regarding manufacturing locations (i.e., pool all production in the domestic market vs. diversify production to both markets). Our numerical study reveals additional insights regarding how the manufacturer's capacity investment levels in the two markets vary under the two regulatory settings. Subsequently, we investigate how the changes in capacity investment levels influence service level and public health outcome. Examining the implications of such mandates on the domestic market, overseas market, and global system provides a comprehensive understanding of the potential macro-level consequences of these mandates, including possible disparities of vaccine availability and public health outcomes across locations.

The remainder of this chapter is organized as follows. In section 5.2, we introduce our analytical framework that captures the decision settings of the manufacturer and briefly discuss some structural results of our analytical models. Next, in section 5.3, we present a numerical study that investigates the implications of the two regulatory mandates on the manufacturer's capacity investment strategies and corresponding impacts on service level and public health outcome. We conclude with a discussion in section 5.4.

5.2 Analytical Models and Analysis

We consider a profit-maximizing vaccine manufacturer that serves random demand over a fixed period in two markets: a domestic market where the manufacturer's existing capacity is located (Country 1) and an overseas market where the manufacturer can build capacity (Country 2).[3] Country i's demand D_i is a random variable with support $[0, d_i]$, where d_i is the population of Country i. We denote $\mathbf{D} = (D_1, D_2)'$ and its joint probability density function as $f(D_1, D_2)$. The manufacturer's problem is to determine the optimal level of production capacity, K_i, to invest in Country i $(i = 1, 2)$. For simplicity, we assume that the unit capacity investment cost is the same across the two markets and is denoted as c. In Country i, the unit manufacturing cost and retail price are denoted as m_i and p_i, respectively. We assume that vaccines produced in Country 1 can be transported to Country 2 at a unit transshipment cost of t, but shipment from Country 2 to Country 1 is not feasible. We focus on the one-directional transshipment scenario to highlight the implications of unilateral regulatory mandates and maintain the tractability of our models. In this production and transportation network, the manufacturer has three fulfillment options. Domestic demand can only be satisfied by vaccines produced in the domestic country, but overseas demand can be satisfied by vaccines produced in the overseas country and transshipped from the domestic country. When production and consumption both occur within the domestic country or the overseas country, the fulfillment option is denoted as D or O, respectively. Fulfillment option T denotes the opportunity to supply the overseas country through cross-border transportation of vaccines. Figure 5.1 illustrates these fulfillment options.

[3]The case of deterministic demand is discussed in the Appendix.

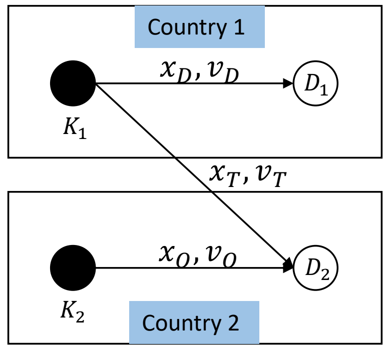


Figure 5.1: Illustration of Vaccine Fulfillment Options

5.2.1 Base Case

We first consider the base case where no government mandates are imposed to limit vaccine export from the domestic country. The sequence of events in this case is as follows. In the first stage, before the random demands D_i are realized, the manufacturer decides the capacity investment levels $\mathbf{K} = (K_1, K_2)'$. In the second stage, after observing the realization of D_i, the manufacturer determines fulfillment quantities associated with the three fulfillment options $\mathbf{x} = (x_D, x_O, x_T)'$, subject to the capacity constraints set by $\mathbf{K}$. To simplify notation, we define v_j as the net value (profitability) per unit of vaccine fulfilled through option j. Specifically, we have:

$$v_j \equiv \begin{cases} p_1 - m_1, & \text{for } j = D \\ p_2 - m_2, & \text{for } j = O \\ p_2 - m_1 - t, & \text{for } j = T \end{cases} .$$

We assume $v_j > c$.

The above-described setting can be modeled as a stochastic programming problem with recourse. It can be solved through backward induction, starting with the second-stage problem. The second-stage problem takes the first-stage capacity decisions $\mathbf{K}$ as input and determines the optimal production and transportation plan. This problem is deterministic and can be represented as:

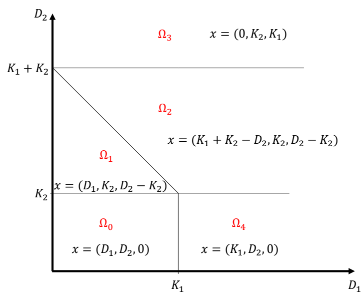
$$\pi(\mathbf{K}, \mathbf{D}) = \max_{\mathbf{x}} \mathbf{v}'\mathbf{x}$$

$$\text{subject to } x_D + x_T \leqslant K_1,\ x_O \leqslant K_2,$$
$$x_D \leqslant D_1,\ x_O + x_T \leqslant D_2.$$

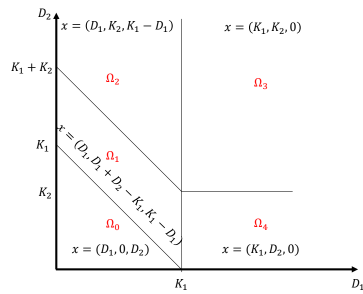
The optimal solution follows a greedy policy, fulfilling demand across the three options based on the ordering of v_j ($j = D, O, T$). To illustrate the manufacturer's optimal decisions in the second stage, it is useful to classify all possible combinations of v_j's into six scenarios based on which demand fulfillment option is the most profitable. When the overseas fulfillment option dominates, there are two possibilities: either the transshipment fulfillment option is the second-most profitable ($v_D < v_T < v_O$), or the domestic fulfillment option is the second-most profitable ($v_T < v_D < v_O$). We denote the former scenario as OT and the latter as OD, with each pair of letters indicating the two fulfillment options with the highest net value in descending order. Similarly, we use DT to denote $v_O < v_T < v_D$ and DO to denote $v_T < v_O < v_D$. When the transshipment fulfillment option dominates, we use a different notation for the second letter to indicate how large v_D is: TM denotes the scenario where v_D is moderately high ($v_T < v_D + v_O$), while TE denotes the scenario where v_D is extremely high ($v_T > v_D + v_O$). The optimal production and transportation plans under each scenario, based on inputs $\mathbf{K}$ and $\mathbf{D}$, are shown in Figure 5.2.

Several patterns emerge from the results shown in Figure 5.2. When the overseas fulfillment option dominates, the second-stage solutions of OT and OD scenarios only differ when the demand is relatively high (regions Ω_2 and Ω_3). In contrast, when the domestic fulfillment option dominates, the second-stage solutions of DT and DO scenarios only differ when the demand is relatively low (regions Ω_0 and Ω_1). When the transshipment fulfillment option dominates, TM and TE scenarios only differ in regions where the demand in the overseas market is in the low to intermediate range and the demand in the domestic market is not too low.

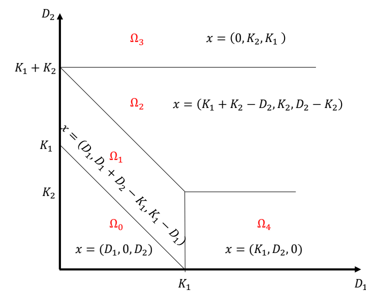
Turning to the first-stage problem, here the decision variable is the capacity investment level K_i for each location i. The manufacturer chooses these levels to optimize expected profit before demand is realized, as formally specified below.



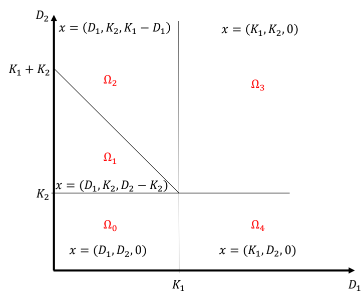
(1) OT: $v_D < v_T < v_O$



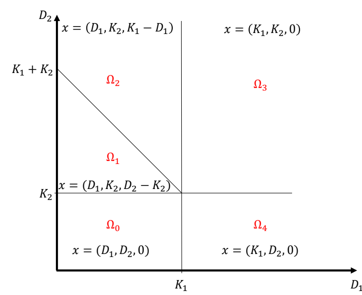
(3) DT: $v_O < v_T < v_D$



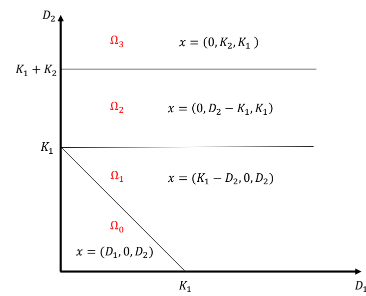
(5) TM: $v_T > \max\{v_D, v_O\}$ and $v_T < v_D + v_O$



(2) OD: $v_T < v_D < v_O$



(4) DO: $v_T < v_O < v_D$



(6) TE: $v_T > \max\{v_D, v_O\}$ and $v_T > v_D + v_O$

Figure 5.2: Fulfilled Vaccine Quantities by Fulfillment Options under Different Scenarios

$$\Pi_{BC}(K_1, K_2) = \max_{K_1, K_2} \int_0^{d_2} \int_0^{d_1} \pi(\mathbf{K}, \mathbf{D}) f(D_1, D_2)\, dD_1\, dD_2 - c(K_1 + K_2)$$

$$\text{subject to} \;\; K_i \geqslant 0, i = 1, 2.$$

To solve this first-stage problem, we first focus on the structural property of its expected profit function, which is captured by the following lemma:

Lemma 5.1. *The manufacturer's expected profit function under the base case is jointly concave in* $\mathbf{K}$.

Building on this property, our analytical analysis focuses on identifying when the manufacturer should invest capacity only at the domestic location vs. both locations. We refer to the first strategy as 'pool' and the second as 'diversify'. To facilitate the presentation, we introduce the notation $\tilde{K}^{DO} = (\tilde{K}_1^{DO}, 0)$, which represents the boundary solution in scenario DO. The manufacturer's optimal capacity commitment strategy is then characterized in the following proposition.

Proposition 5.1. *The manufacturer's optimal capacity commitment strategy under the base case scenario is as follows:*

(1) Diversify when

- *(a)* $v_O > \max\{v_D, v_T\}$, *or*
- *(b)* $v_T < v_O < v_D$ *and* $c < v_O - v_T P_1$, *where* $P_1 = Pr(D_1 + D_2 \leqslant \tilde{K}_1^{DO})$;

(2) Pool when

- *(a)* $v_O < v_T$, *or*
- *(b)* $v_T < v_O < v_D$ *and* $c > v_O - v_T P_1$.

Proposition 5.1 highlights that the relative profitability of the three fulfillment options determines whether the manufacturer should diversify. When the overseas fulfillment option dominates (i.e., $v_O > \max\{v_D, v_T\}$, in scenarios OT and OD), it is always optimal to diversify. In contrast, when the overseas fulfillment option is less profitable than the transshipment fulfillment option (i.e., $v_O > \max\{v_D, v_T\}$, in scenarios DT, TM, and TE), it is always optimal to pool capacity in the domestic country. When the overseas fulfillment option is moderately profitable and the domestic fulfillment option dominates (i.e., $v_T < v_O < v_D$), the manufacturer's optimal diversification strategy depends on the unit capacity investment cost. When this cost is relatively low, it is better to diversify; when this cost is relatively high, it is better to consolidate all the capacity in the domestic country and take advantage of the risk-pooling effect.

5.2.2 Random Ban

We now consider how the manufacturer's decision problem changes when facing the domestic government's mandates to regulate vaccine export in the hope of improving domestic vaccine availability. We begin with the case of a random ban (RB). Under this scenario, the domestic government may issue an export ban that prohibits the manufacturer from exporting any vaccine to the overseas country, but there is uncertainty regarding whether the government will activate this ban. We capture this uncertainty by a random event with a known probability. This broad and preemptive measure might be utilized when the domestic government cannot accurately track and measure domestic demand. As a result, the government may want to err on the side of caution.

The sequence of events in this setting differs from that in the base case in the following ways. First, before the manufacturer makes capacity investment decisions, it is aware that the government may impose an export ban with a probability δ. Second, after the manufacturer makes the capacity investments, the domestic government's export ban status is realized and the manufacturer observes the demand in the two countries. The introduction of this mandate changes the manufacturer's second-stage problem by adding another constraint $x_T = 0$ with a probability δ. The manufacturer's optimal fulfillment plan if the export ban is activated is shown in Figure 5.3. We denote profit in this circumstance as $\Pi_B(K_1, K_2)$. It is straightforward to see that the manufacturer's expected profit under the random ban is the weighted average of its expected profit under the base case and expected profit when the export ban is activated, i.e., $\Pi_{RB}(K_1, K_2) = (1-\delta)\Pi_{BC}(K_1, K_2) + \delta\Pi_B(K_1, K_2)$.

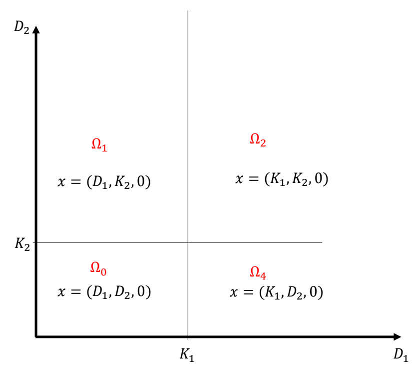


Figure 5.3: Fulfilled Vaccine Quantities by Fulfillment Options when the Export Ban is Activated

To solve the manufacturer's problem, we again start by examining the structural properties of the manufacturer's expected profit function. The results are presented below.

Lemma 5.2. *The manufacturer's expected profit function under the random ban is jointly concave in* $\mathbf{K}$.

To characterize the manufacturer's optimal first-stage capacity decisions, we again introduce additional notation. Let $\hat{K}^s = (\hat{K}_1^s, 0)$ be the boundary solution in scenario $s \in \{DO, DT, TM, TE\}$ under the random ban. The following result characterizes the manufacturer's optimal capacity commitment strategy in this case.

Proposition 5.2. *The manufacturer's optimal capacity commitment strategy under the random ban scenario is as follows:*

(1) Diversify when

- *(a)* $v_O > \max\{v_D, v_T\}$, *or*
- *(b)* $v_T < v_O < v_D$ *and* $c < v_O - (1-\delta)v_T P_1^{DO}$, *where* $P_1^{DO} = Pr(D_1 + D_2 \leqslant \hat{K}_1^{DO})$, *or*
- *(c)* $v_O < v_T < v_D$ *and* $c < v_O\left(1 - (1-\delta)P_1^{DT}\right)$, *where* $P_1^{DT} = Pr(D_1 + D_2 \leqslant \hat{K}_1^{DT})$, *or*
- *(d)* $\max\{v_D, v_O\} < v_T < v_D + v_O$ *and* $c < v_O\left(1 - (1-\delta)P_1^{TM}\right) - (1-\delta)(v_T - v_D)P_2^{TM}$, *where* $P_1^{TM} = Pr(D_1 + D_2 \leqslant \hat{K}_1^{TM})$ *and* $P_2^{TM} = Pr(D_2 \leqslant \hat{K}_1^{TM}) - P_1^{TM}$, *or*
- *(e)* $v_T > v_D + v_O$ *and* $c < v_O\left(\delta - (1-\delta)P_3^{TE}\right)$, *where* $P_3^{TE} = Pr(D_2 > \hat{K}_1^{TE})$;

(2) Pool when

- *(a)* $v_T < v_O < v_D$ *and* $c > v_O - (1-\delta)v_T P_1^{DO}$, *or*
- *(b)* $v_O < v_T < v_D$ *and* $c > v_O\left(1 - (1-\delta)P_1^{DT}\right)$, *or*
- *(c)* $\max\{v_D, v_O\} < v_T < v_D + v_O$ *and* $c > v_O\left(1 - (1-\delta)P_1^{TM}\right) - (1-\delta)(v_T - v_D)P_2^{TM}$, *or*
- *(d)* $v_T > v_D + v_O$ *and* $c > v_O\left(\delta - (1-\delta)P_3^{TE}\right)$.

Comparing Propositions 5.1 and 5.2, we see that the introduction of a random ban leads to important differences in the manufacturer's optimal capacity commitment strategy. When the profitability of the transshipment fulfillment option is higher than that of the overseas fulfillment option (i.e., $v_O < v_T$), it may no longer be optimal to pool all capacity in the domestic country, because the transshipment fulfillment option will be cut off if the export ban is activated. When the unit capacity investment is relatively low, it becomes advantageous for the manufacturer to diversify under such circumstances to counteract the potential export ban. In contrast, when the overseas fulfillment option dominates (i.e., $v_O > \max\{v_D, v_T\}$), the manufacturer's optimal strategy does not change, and diversifying is still the preferred option. We formally summarize these insights in the following corollary.

Corollary 5.1. *The introduction of the random ban causes the manufacturer to switch its capacity commitment strategy from pooling to diversifying when:*

(a) In the DT scenario and $c < v_O\left(1-(1-\delta)P_1^{DT}\right)$, *or*

(b) In the DO scenario and $v_O - v_T P_1 < c < v_O - (1-\delta)v_T P_1^{DO}$, *or*

(c) In the TM scenario and $c < v_O\left(1-(1-\delta)P_1^{TM}\right) - (1-\delta)(v_T - v_D)P_2^{TM}$, *or*

(d) In the TE scenario and $c < v_O\left(\delta-(1-\delta)P_3^{TE}\right)$.

5.2.3 Priority Requirement

We next consider the case of a priority requirement (PR) mandate. In this case, the domestic government introduces a mandate that requires the manufacturer to prioritize domestic demand. Under this mandate, vaccine export to the overseas country is only allowed after all domestic demand has been satisfied. Unlike a random ban, this mandate is more surgical and does not involve any uncertainty associated with the activation of this policy.

A priority requirement is usually issued before capacity decisions are made. Therefore, the effect of this mandate manifests in the second stage of the manufacturer's decision problem by further restricting the value of x_D to be one of two cases such that $x_D = \min\{D_1, K_1\}$. This restriction does not change the nature of the solution but reduces the number of scenarios to consider under PR. When the domestic fulfillment option is more profitable than the transshipment fulfillment option (i.e., $v_D > v_T$), there is no change in the manufacturer's expected profit function, since the domestic market is always supplied first. Thus, $\Pi_{PR}^{OD}(K_1, K_2) = \Pi_{BC}^{OD}(K_1, K_2)$, $\Pi_{PR}^{DO}(K_1, K_2) = \Pi_{BC}^{DO}(K_1, K_2)$, and $\Pi_{PR}^{DT}(K_1, K_2) = \Pi_{BC}^{DT}(K_1, K_2)$. As a result, the introduction of PR does not change the manufacturer's optional capacity investment decisions in those scenarios. However, when the transshipment fulfillment option is more lucrative (i.e., $v_D < v_T$), the manufacturer's priority shifts from exporting to satisfying domestic demand, in order to comply with the PR mandate. This change makes the manufacturer's expected profit function under PR differ from that under BC: $\Pi_{PR}^{OT}(K_1, K_2) = \Pi_{BC}^{OD}(K_1, K_2)$ and $\Pi_{PR}^{TM}(K_1, K_2) = \Pi_{PR}^{TE}(K_1, K_2) = \Pi_{BC}^{DT}(K_1, K_2)$. Therefore, the manufacturer might need to adjust its capacity investment strategies in response to the mandate imposed by the domestic government.

To characterize the manufacturer's optimal capacity commitment strategy, we again start by examining whether the expected profit function is jointly concave in $\mathbf{K}$. Unfortunately, this is not the case for the priority requirement (a counterexample is provided in the Appendix), so it becomes challenging to obtain a closed-form solution. We resort to numerical analyses to help us identify the manufacturer's optimal solutions.

5.3 Numerical Study

In this section, we present a numerical study to understand how the two types of regulatory mandates influence the manufacturer's optimal capacity investment strategies. These analyses not only help compare the manufacturer's optimal responses to these mandates, but also allow us to evaluate how changes in the manufacturer's operations impact the vaccine service level and associated public health outcome.

5.3.1 Parameter Space Setup

The key parameters of the manufacturer's decision problem include the net value of each vaccine fulfillment option v_j, the unit capacity investment cost c, the likelihood that an export ban will be enacted δ, and the populations of the two countries d_i. Our parameters are grounded in the numerical examples of Lu and Van Mieghem (2009) but extend to a wider range of values.

We consider a wide range of profitability levels for the fulfillment options, with $v_D, v_O, v_T \in \{5, 7, 9, \cdots, 25\}$. As our analytical results suggest that the manufacturer's capacity commitment strategy is sensitive to the underlying unit capacity investment cost, we consider a more granular set of $c \in \{1, 1.2, 1.4, \cdots, 25\}$. For the random ban case, we incorporate five different levels of likelihood that an export ban will be activated: $\delta \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$. As the insights are quite consistent across different

δ values, we only report the results of the $\delta = 0.5$ case.

We assume throughout this numerical study that vaccine demand in the two countries is independent and uniformly distributed with $D_i \sim [0, d_i]$. To evaluate how the differences in the two countries' populations may influence the results, we consider three sets of settings: (i) the countries have equal populations – $d_1 = d_2 = 100$; (ii) the domestic country has the larger population – $d_1 = 100$ and $d_2 \in \{50, 60, 70, 80, 90\}$; and (iii) the domestic country has the smaller population – $d_1 \in \{50, 60, 70, 80, 90\}$ and $d_2 = 100$. In this section, we first focus on the results of setting (i) with equal populations and then summarize how the main insights differ when the two countries have different populations.

5.3.2 Influence on Capacity Commitment Strategy and Capacity Levels

We begin by investigating how a regulatory mandate will influence the manufacturer's optimal capacity commitment strategy and capacity levels. For the random ban condition, we are primarily interested in evaluating the relative proportion of cases in which the manufacturer needs to switch from pooling to diversifying. For the priority requirement condition, we are interested in gaining insights into the structure of the optimal solution, including how the mandate shifts its capacity commitment strategies relative to the base case.

Table 5.1 summarizes the impact of the two regulatory mandates on the manufacturer's capacity commitment strategies in different scenarios. For the random ban condition, the results confirm our Corollary 5.1 that there are only three possibilities: the manufacturer either stays with its diversifying or pooling strategy or switching from pooling to diversifying. What is important in the table is that the manufacturer needs to change its strategy in many cases. On the other hand, for the priority requirement condition, we see that the manufacturer rarely needs to switch from pooling to diversifying (only 1.1% of TM). In scenarios other than TM, it stays with either diversifying or pooling. Across the influence of the two regulatory mandates, it appears that a priority requirement requires fewer strategic changes since the manufacturer usually does not need to worry about building capacities in the overseas country and can focus primarily on adjusting capacity investment levels instead. To understand how the manufacturer should tweak its capacity levels, we continue our analysis and examine in each setting, whether the manufacture should increase or decrease its capacity investment levels in the two countries.

Table 5.1: Impact of Regulatory Mandates on Capacity Commitment Strategy

	Influence of Random Ban			Influence of Priority Requirement		
Scenario	Stick to Diversifying (%)	Stick to Pooling (%)	Switch (%)	Stick to Diversifying (%)	Stick to Pooling (%)	Switch (%)
OT	100			100		
OD	100			100		
DO	97.4		2.6	97.4	2.6	
DT		14.9	85.1		100	
TM		12.1	87.9		98.9	1.1
TE		32.9	67.1		100	

Table 5.2 shows how the manufacturer's optimal capacity investment level changes in the domestic country, the overseas country, and the global level ($K_g = K_1 + K_2$). The results are organized by different scenarios and capacity commitment strategies corresponding to Table 5.1. Each column displays the proportion of cases in which the capacity level at the location increases, and the corresponding proportion of cases that witness a decrease is listed in parentheses as a reference.[4] The column "Case Percentage" indicates the relative weight of each subset in the *entire parameter space* to help us understand the relative frequency of encountering such settings. We see that the pattern is relatively straightforward for RB. The manufacturer's capacity investment in the domestic country always decreases since the optional value of excess capacity in the domestic country is hampered by the prospect of a ban. In addition, the manufacturer chooses to invest more in the overseas country as long as it is profitable to diversify. Otherwise, the manufacturer simply reduces its domestic capacity without adding new capacity in the overseas country. Although the two forces point to different directions, the net global capacity investment level increases in more cases when diversifying is the optimal strategy.

The pattern for the priority requirement is different. When it is optimal to stick to pooling, the manufacturer's optimal domestic capacity investment level almost always

[4]Since the manufacturer's decisions do not change in OD, DO, and DT scenarios, the results of these scenarios are noted as "–" in the table and subsequent tables of outcome measures.

increases, resulting in a global capacity increase. When it is optimal to stay with diversifying, the optimal capacity level in the overseas country increases, but the domestic capacity level may increase or decrease. It appears that the forces increasing capacity investment dominate such that the global capacity investment usually increases in such scenarios. In the rare cases in which the manufacturer needs to switch from pooling to diversifying, part of the domestic capacity is shifted to the overseas market.

Comparing the two panels in Table 5.2, we see that the two regulatory mandates influence the manufacturer's optimal capacity investment levels in different ways. A random ban induces avoidance of building up higher capacity in the domestic country, so the manufacturer either shifts some domestic capacity to the overseas country or reduces domestic capacity without adding overseas capacity. In contrast, under the priority requirement condition, since excess domestic capacity can still be used to satisfy overseas demand, this mandate in general encourages the manufacturer to increase domestic capacity investment. When the overseas and transshipment fulfillment options are the top two profit avenues (i.e., the OT scenario), it is advantageous to increase overseas capacity. However, adding more domestic capacity at the same time may be a good strategy, as it provides an option to take advantage of the situations in which the domestic demand is low and overseas demand is high without over-committing capacity in the overseas country.

To summarize our findings so far, we see that regulatory risks can influence the manufacturer's operations strategy. The two mandates we examine can both induce the manufacturer to change its capacity strategy from pooling to diversifying. As a result, some domestic capacity is shifted to the overseas country. In fact, under a random ban, even if the manufacturer stays with its original strategy as in the base case, the domestic capacity level still decreases. Under a priority requirement, the domestic capacity may also decrease when the manufacturer has to expand its capacity diversification in OT and TM scenarios. Given the manufacturer's strategic responses to the domestic government's regulatory mandates, domestic capacity level and even global capacity level may decrease. Hence, these changes may undermine the domestic government's ambition to boost domestic vaccine supply. However, it is important to note that the regulatory mandates introduced by the domestic government help re-route some of the vaccine doses that would have been shipped to the overseas country if there

Table 5.2: Impact of Regulatory Mandates on Capacity Investment Levels

Influence of Random Ban						Influence of Priority Requirement					
Scenario	Strategy Status	Case Percentage	K_1 increase (decease)	K_2 increase (decease)	K_g increase (decease)	Scenario	Strategy Status	Case Percentage	K_1 increase (decease)	K_2 increase (decease)	K_g increase (decease)
OT	Stick to Diversifying	15.58	0 (100)	100 (0)	69.2 (30.8)	OT	Stick to Diversifying	15.58	42.5 (57.5)	100 (0)	86.3 (13.7)
OD	Stick to Diversifying	15.58	0 (100)	100 (0)	77.2 (22.8)	OD	Stick to Diversifying	15.58	--	--	--
DO	Switch	0.41	0 (100)	100 (0)	26 (74)	DO	Stick to Pooling	0.41	--	--	--
	Stick to Diversifying	15.17	0 (100)	100 (0)	89.9 (10.1)		Stick to Diversifying	15.17	--	--	--
DT	Stick to Pooling	2.32	0 (100)	0 (0)	0 (100)	DT	Stick to Pooling	15.58	--	--	--
	Switch	13.26	0 (100)	100 (0)	54.9 (45.1)	TM	Stick to Pooling	29.78	99 (1)	0 (0)	99 (1)
TM	Stick to Pooling	3.64	0 (100)	0 (0)	0 (100)		Switch	0.33	2.1 (97.9)	100 (0)	47.6 (52.4)
	Switch	26.47	0 (100)	100 (0)	53.8 (46.2)	TE	Stick to Pooling	7.56	100 (0)	0 (0)	100 (0)
TE	Stick to Pooling	2.49	0 (100)	0 (0)	0 (100)						
	Switch	5.07	0 (100)	100 (0)	63.9 (36.1)						

were no export control. For this reason, these mandates may still improve domestic vaccine supply by increasing the effective utilization of domestic capacity directed to serve domestic demand. To fully understand the efficacy of the domestic government's regulatory mandates in promoting the welfare of domestic citizens, we need to further examine how changes in the manufacturer's capacity investment levels impact service level and public health outcome.

5.3.3 Implications for Service Level and Public Health Outcome

To assess the policy implications of the two regulatory mandates, we start by looking at how service level changes as a result of the manufacturer's strategic responses to the mandates. Specifically, we focus on fill rate, which captures the proportion of demand that is satisfied during the season. Given the committed capacity levels (K_1, K_2), the expected fill rate $\mathbb{E}FR_i$ of the domestic country ($i = 1$), overseas country ($i = 2$), and global system ($i = g$) are defined as:

$$\mathbb{E}FR_i(K_1, K_2) \equiv \begin{cases} \int_0^{d_2}\int_0^{d_1} f(D_1, D_2)\frac{x_D}{D_1}\, dD_1\, dD_2 & i = 1 \\ \int_0^{d_2}\int_0^{d_1} f(D_1, D_2)\frac{x_O + x_T}{D_2}\, dD_1\, dD_2 & i = 2 \\ \int_0^{d_2}\int_0^{d_1} f(D_1, D_2)\frac{x_D + x_O + x_T}{D_1 + D_2}\, dD_1\, dD_2 & i = g. \end{cases}$$

Table 5.3 displays the results of our analysis on fill rate. Under a random ban, although our previous analysis shows that the domestic capacity level always decreases, the domestic fill rate does not always suffer. While the fill rate indeed decreases in OD and DO scenarios, it may stay the same in some of the DT cases. Moreover, in other scenarios, we actually observe a considerable proportion of cases (as high as 81%) where the domestic fill rate increases. On the other hand, overseas fill rate only increases in OD, DO, and DT scenarios, where the domestic fill rate does not increase. The net effect on the global fill rate is rather detrimental, since the proportion of cases with an increased global fill rate is quite low.

Under a priority requirement, it turns out that the domestic fill rate in general increases. At the same time, the overseas fill rate never increases, although the global fill rate is more likely to increase than to decrease. Comparing the impact of the two regulatory mandates, we see that they may be surprisingly effective in promoting the domestic fill rate. However, this benefit comes at the expense of decreased fill rate in the overseas country, potentially increasing the disparity across the two countries.

Once we understand how service level is impacted, it is also important to evaluate the implications for public health outcome. While the analysis on fill rate reveals the performance from the operations perspective, additional analysis on how vaccine availability influences public health is needed in our context because the fill rate cannot capture the unique value of vaccines in a pandemic.

To fully appreciate the nuances involved in this context, we first need to understand how vaccination influences the population at a macro level. In the epidemiology literature, the likelihood of being infected, $\mu(\theta)$, is modeled as a decreasing function in θ, the proportion of vaccinated people in the population. If the vaccine is 100% effective, once θ reaches a critical threshold $\hat{\theta}$, the likelihood of being infected drops to a negligible

Table 5.3: Impact of Regulatory Mandates on Service Level (Fill Rate)

Influence of Random Ban

Scenario	Strategy Status	Case Percentage	Country	Increasing	No Change	Decreasing
OT	Stick to Diversifying	15.58	1	81.9		18.1
			2			100
			g			100
OD	Stick to Diversifying	15.58	1			100
			2	8.9		91.1
			g			100
DO	Switch	0.41	1			100
			2	60.4		39.6
			g			100
	Stick to Diversifying	15.17	1			100
			2	31.9		68.1
			g			100
DT	Stick to Pooling	2.32	1		6.6	93.4
			2			100
			g			100
	Switch	13.26	1		14.7	85.3
			2	15.8		84.2
			g	1.4		98.6
TM	Stick to Pooling	3.64	1	58.4		41.6
			2			100
			g			100
	Switch	26.47	1	95.8		4.2
			2			100
			g	16		84
TE	Stick to Pooling	2.49	1	66.6		33.4
			2			100
			g			100
	Switch	5.07	1	25.6		74.4
			2			100
			g			100

Influence of Priority Requirement

Scenario	Strategy Status	Case Percentage	Country	Increasing	No Change	Decreasing
OT	Stick to Diversifying	15.58	1	94.2		5.8
			2			100
			g	74.9		25.1
OD	Stick to Diversifying	15.58	1	--	--	--
			2	--	--	--
			g	--	--	--
DO	Stick to Pooling	0.41	1	--	--	--
			2	--	--	--
			g	--	--	--
	Stick to Diversifying	15.17	1	--	--	--
			2	--	--	--
			g	--	--	--
DT	Stick to Pooling	15.58	1	--	--	--
			2	--	--	--
			g	--	--	--
TM	Stick to Pooling	29.78	1	100		
			2			100
			g	99		1
	Switch	0.33	1	100		
			2			100
			g	28.7		71.3
TE	Stick to Pooling	7.56	1	100		
			2			100
			g	100		

level and "herd immunity" is achieved. Specifically,

$$\mu(\theta) \equiv \begin{cases} 1 - \dfrac{1}{R_0(1-\theta)} & \theta < \hat{\theta} \\ 0 & \theta \geqslant \hat{\theta}, \end{cases}$$

in which R_0 is the basic reproduction number for this disease and the corresponding herd immunity threshold $\hat{\theta} = 1 - 1/R_0$ (Fine et al. 2011). In other words, it is not necessary for everyone in a population to be vaccinated in order for that population to be fully protected. Nevertheless, full population protection requires that there is sufficient demand from citizens who are willing to get the vaccine and sufficient supply to satisfy such demand.

The non-linear form of the infection rate function has important implications for public health outcome: one additional vaccine dose beyond the herd immunity threshold is not valuable to the protected population, but it could generate a much larger impact if it could be diverted to another country that has not yet achieved herd immunity. A suitable measure for public health outcome can allow us to better capture these dynamics.

In public health literature, the quality-adjusted life year (QALY) has been used routinely as a common measure to compare healthcare outcomes (Whitehead and Ali 2010). This measure takes into account both mortality and morbidity to provide an aggregate measure of how patients' life quality has been impacted by a disease. To approximate the QALY measure at a population level in our context, we first classify the population into different groups based on health status. If we denote the infection fatality rate as σ, then the total population d can be divided into four groups: those who are vaccinated (x), those who are not vaccinated but not infected ($(d-x)(1-\mu(x/d))$), those who are infected and do not survive ($(d-x)\mu(x/d)\sigma$), and those who are infected but survive ($(d-x)\mu(x/d)(1-\sigma)$). Next, we normalize the QALY of healthy people (either vaccinated or not vaccinated but not infected) as 1, that of surviving patients as γ, and that of those who die as 0. Note that $\gamma < 1$ reflects the reduction in life quality resulting from long-haul syndrome (e.g., Vanichkachorn et al. 2021, Health 2021). The aggregated QALY, as a function of vaccinated people x, can be represented as:

$$\begin{aligned} QALY(x) &= x \cdot 1 + (d-x)(1-\mu(x/d)) \cdot 1 + (d-x)\mu(x/d)(1-\sigma)\cdot\gamma \\ &= d - (d-x)(1-\gamma+\sigma\gamma)\mu(x/d) \\ &= \begin{cases} d-(d-x)(1-\gamma+\sigma\gamma)\dfrac{R_0(1-x/d)-1}{R_0(1-x/d)} & x/d < 1-1/R_0 \\ d & x/d \geqslant 1-1/R_0 \end{cases} \\ &= \begin{cases} (1-\gamma(1-\sigma))x + \dfrac{1+\gamma(1-\sigma)(R_0-1)}{R_0}d & x/d < 1-1/R_0 \\ d & x/d \geqslant 1-1/R_0. \end{cases} \end{aligned}$$

The expected quality-adjusted life year $\mathbb{E}QALY$ in the domestic country, the overseas country, and the global system can then be written as:

$$\mathbb{E}QALY_i(K_1,K_2) \equiv \begin{cases} \displaystyle\int_0^{d_2}\int_0^{d_1} f(D_1,D_2)QALY(x_D)\,dD_1\,dD_2 & i=1 \\ \displaystyle\int_0^{d_2}\int_0^{d_1} f(D_1,D_2)QALY(x_O+x_T)\,dD_1\,dD_2 & i=2 \\ \mathbb{E}QALY_1(K_1,K_2)+\mathbb{E}QALY_2(K_1,K_2) & i=g. \end{cases}$$

In our numerical study, we set $\sigma = 5\%$ and $R_0 = 2.5$.[5] We choose $\gamma = 0.8$ to capture a moderate reduction in life quality for COVID-19 patients.

Table 5.4 shows how QALYs change when the domestic government introduces a random ban or a priority requirement. Compared with the fill rate results in Table 5.3, we see that there are significantly more cases in which the QALYs do not change, potentially due to the non-linear nature of herd immunity. Under a random ban, despite the general trend of decreased domestic capacity, we observe that domestic QALYs still increase in more than half of the cases in certain scenarios. However, in these scenarios, the number of cases with more favorable domestic outcomes generally drops when the criterion switches from fill rate to QALYs. The opposite occurs at the global level, as we see that global QALYs may increase more often. This discrepancy is primarily driven

[5] 2019 Novel Coronavirus Parameter Estimates, MIDAS 2019 Novel Coronavirus GitHub Repository, MIDAS Coordination Center (MCC), `https://github.com/midas-network/COVID-19/tree/master/parameter_estimates/2019_novel_coronavirus`.

by the fact that at the global level, QALYs are fully substitutable but fill rates are not. A unit of QALY increase in the domestic country can thus fully offset a unit of QALY decrease in the overseas country. However, if the fill rates of the two countries change in different directions at the same rate, the resulted global fill rate can still decrease. In contrast, under a priority requirement, the proportions of cases with increased QALYs in the domestic country and the global system are not as high as the proportions of cases with increased fill rate. This does not result in a significant drop in QALYs, since we see many cases fall into the "No Change" category instead of the "Decreasing" category.

Table 5.4: Impact of Regulatory Mandates on Public Health Outcome (QALYs)

Influence of Random Ban						
Scenario	Strategy Status	Case Percentage	Country	Increasing	No Change	Decreasing
OT	Stick to Diversifying	15.58	1	61.2	10.1	28.7
			2		69.2	30.8
			g	53	10.1	36.9
OD	Stick to Diversifying	15.58	1		64	36
			2	29.5	63.5	7
			g	11.1	54.8	34.1
DO	Switch	0.41	1		40.2	59.8
			2	8.9		91.1
			g	0.6		99.4
	Stick to Diversifying	15.17	1		87.1	12.9
			2	51.1	32.9	16
			g	45.3	32.9	21.8
DT	Stick to Pooling	2.32	1		87	13
			2			100
			g			100
	Switch	13.26	1		94.2	5.8
			2	25.8	4.4	69.8
			g	25.8	4.4	69.8
TM	Stick to Pooling	3.64	1	63.2		36.8
			2			100
			g			100
	Switch	26.47	1	88.7	3.1	8.2
			2		26.5	73.5
			g	39	2.9	58.1
TE	Stick to Pooling	2.49	1	67.3		32.7
			2			100
			g			100
	Switch	5.07	1	33		67
			2		21.9	78.1
			g	1.8		98.2

Influence of Priority Requirement						
Scenario	Strategy Status	Case Percentage	Country	Increasing	No Change	Decreasing
OT	Stick to Diversifying	15.58	1	81.8	10.1	8.1
			2		60.9	39.1
			g	77.2	10.1	12.8
OD	Stick to Diversifying	15.58	1	--	--	--
			2	--	--	--
			g	--	--	--
DO	Stick to Pooling	0.41	1	--	--	--
			2	--	--	--
			g	--	--	--
	Stick to Diversifying	15.17	1	--	--	--
			2	--	--	--
			g	--	--	--
DT	Stick to Pooling	15.58	1	--	--	--
			2	--	--	--
			g	--	--	--
TM	Stick to Pooling	29.78	1	97.2	2.8	
			2		7.7	92.3
			g	96.2	2.8	1
	Switch	0.33	1	98.6		1.4
			2		0.7	99.3
			g	50.3		49.7
TE	Stick to Pooling	7.56	1	99.2	0.8	
			2		15.4	84.6
			g	99.2	0.8	

To further investigate the conditions under which a decreased domestic capacity level translates into better QALYs, we use a figure to illustrate when the domestic QALYs increase, stay the same, or decrease. We choose to focus on the OT scenario because there are high proportions of cases with a decreased domestic capacity level under the two mandates. Figures 5.4 and 5.5 illustrate results for the random ban condition and priority requirement condition, respectively. As we can see from Figure 5.4, when the unit capacity investment cost c is relatively low, there is no change in domestic QALYs. When it increases above a certain threshold, the domestic QALYs are higher under a random ban compared with the base case. However, as it further increases above another threshold, the domestic QALYs are lower compared with the base case. The reason for this pattern is that as c increases, domestic QALYs under the two conditions first stay the same and then decrease. When c is small, QALYs under the two conditions are both high, and thus the random ban does not improve QALYs. When c increases to an intermediate region, QALYs under the base case start to decrease earlier than QALYs under a random ban. When c is relatively large, QALYs under a random ban decrease at a higher rate than QALYs under the base case do. Figure 5.5 shows a similar threshold pattern for the influence of a priority requirement on domestic QALYs, but since the plot only focuses on cases with decreased domestic capacity, we do not observe "No change" cases.

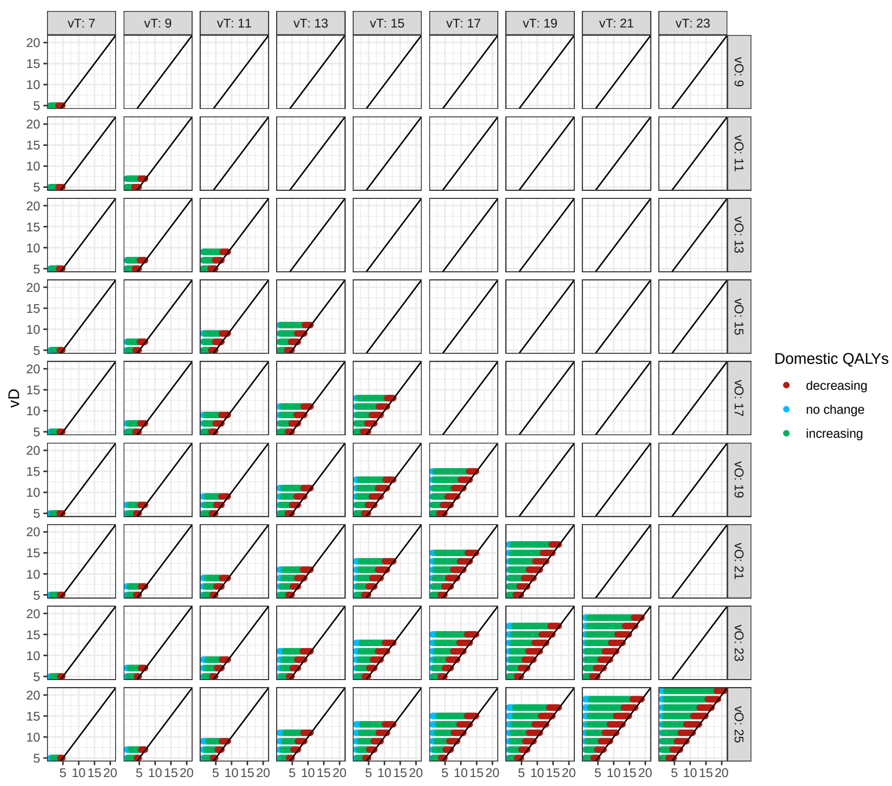


Figure 5.4: Changes in Domestic QALYs under RB in the OT Scenario

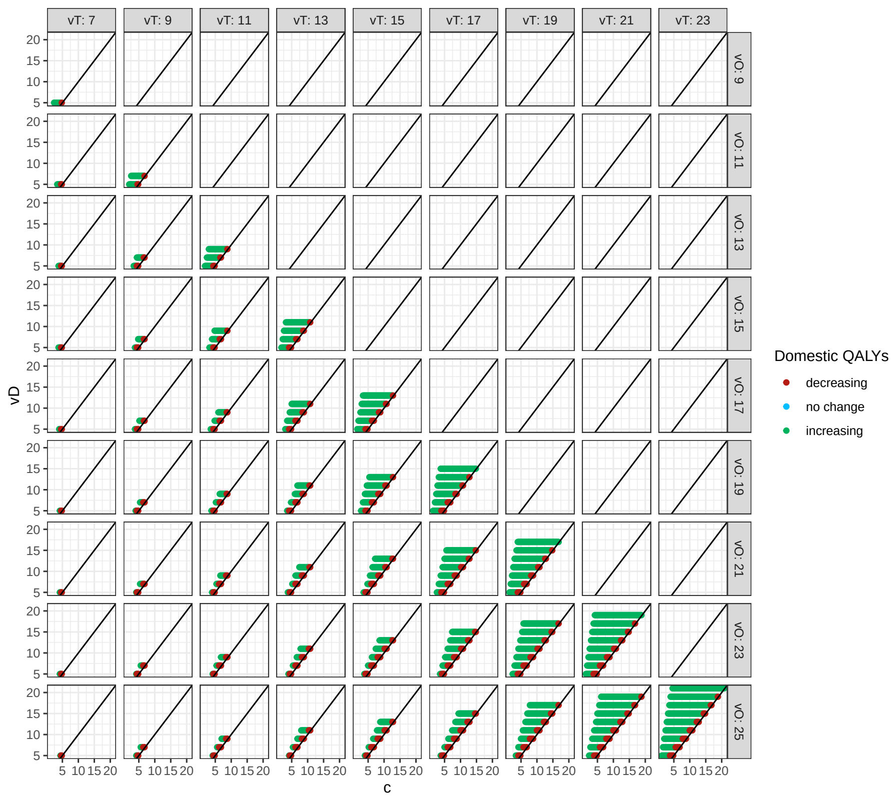


Figure 5.5: Changes in Domestic QALYs under PR in the OT Scenario (Cases with a Decreased Domestic Capacity Only)

5.3.4 Implications for the Domestic Country's Policy Choice

In addition to revealing how the manufacturer responds to the two regulatory mandates by adjusting its global capacity investment plans and how such adjustments influence service level and public health outcome, our analysis provides opportunities to inform the domestic government's policy choice. By being aware of how the manufacturer will react to the two types of regulatory mandates, the domestic government can strategically decide whether implementing a mandate is beneficial.

When the domestic fulfillment option is more profitable than the transshipment fulfillment option (i.e., $v_T < v_D$, OD, DO and DT scenarios), it is clear that a random ban is not an ideal choice for the domestic government, as it never improves either the fill rate or QALYs of the domestic country. Under such scenarios, a priority requirement will not impact the manufacturer's decisions, since it is already in the interest of the manufacturer to prioritize the demand of the domestic country. Hence, the domestic country does not need to implement any regulatory mandate in these scenarios.

When the transshipment fulfillment option dominates the other two options (i.e., $v_T > \max\{v_D, v_O\}$, TM and TE scenarios), the domestic government needs to be careful, since both a random ban and a priority requirement may force the manufacturer to switch its capacity commitment strategy from pooling to diversifying, which in general can lead to worse outcomes for the domestic country. However, under a random ban, even if the manufacturer keeps a pooling strategy, the fill rate and QALYs of the domestic country may still drop in many cases. On the other hand, a priority requirement almost always guarantees that the two measures can be on par with the base case.

The trickiest scenario is when the overseas fulfillment option is the most profitable while the transshipment fulfillment option comes second (i.e., $v_D < v_T < v_O$, OT scenario). While neither a random ban nor a priority requirement induces the manufacturer's strategy change (as it is always preferable to diversify), the domestic capacity level may decrease in many cases under a priority requirement and in all cases under a random ban. Therefore, it is possible that neither of the two mandates can improve domestic welfare.

5.3.5 Influence of Country Characteristics on Capacity Commitment Strategy

Our numerical analysis so far has focused on the setting in which the domestic country and the overseas country have equal populations, which creates a fair ground to compare the effects of the two regulatory mandates under different scenarios. However, allowing the two countries' populations to vary is also important, since the populations determine the upper limit of the potential demand, which may shift the focus of the manufacturer's global capacity plan. By considering the population difference of the two countries, we can not only capture a broader range of situations but also provide additional insights on how the manufacturer's strategies may change. With these considerations in mind, we briefly summarize the numerical analysis results of the settings wherein the domestic country has a larger or smaller population than the overseas country, focusing on the manufacturer's capacity commitment strategy.

When the domestic country has a population advantage (i.e., $d_1 > d_2$), the proportion of cases in which the manufacturer needs to switch from pooling to diversifying under a random ban drops compared with when the two countries have equal populations. The cost threshold that warrants a shift to the diversifying strategy becomes smaller, making it more difficult to justify a strategy change unless the capacity investment cost is meager. In contrast, under a priority requirement, the proportion of cases in which the manufacturer needs to switch due to the mandate actually increases. This result may be counterintuitive, as the conventional wisdom might suggest that the domestic country's population advantage makes pooling more attractive. However, when there is a large gap between the two countries' populations, the domestic capacity level under the base case may already be relatively high. Suppose the manufacturer chooses to add more capacity in the domestic country. In that case, it is likely that even when there is excessive domestic capacity, the overseas demand may not be high enough to consume the spare capacity. These factors result in a lower chance for the manufacturer to take advantage of pooling capacity in the domestic country. As a result, setting up capacity in the overseas country can make the manufacturer better off when the overseas fulfillment option is sufficiently profitable. When the domestic country has a population disadvantage (i.e., $d_1 < d_2$), the pattern is reversed. Under a random ban, the proportion of cases that witness a strategy switch increases as it becomes more important for the manufacturer to safeguard the revenue stream from the overseas market. Under a priority requirement, the proportion of cases in which the manufacturer needs to switch decreases, because the chance of supplying overseas demand with domestic capacity is higher.

5.4 Discussion and Conclusions

In this study, we investigate how regulatory risks arising from national governments' mandates that restrict the flow of vaccine export influence manufacturers' global capacity investment plans. We focus on the capacity planning problem of an international manufacturer that serves random demand in two countries while facing the regulatory risk from the domestic government where it is based. We consider two types of regulatory mandates: a preemptive export ban that is activated randomly (i.e., random ban) and a more targeted measure that prioritizes domestic demand over overseas demand (i.e., priority requirement). Through our analytical models and numerical study, we compare how the manufacturer sets its capacity levels in the two countries under different regulatory settings and how these decisions translate into service level and public health outcome, such as vaccine fill rate and QALYs. Our results reveal how the manufacturer should strategically counteract the two types of regulatory risks and highlight important policy implications that can guide the domestic government's decisions when implementing the mandates.

When facing the prospect of a random ban, the manufacturer needs to carefully consider the plan to set up overseas capacity when the transshipment fulfillment option is more profitable than the overseas fulfillment option. When there is no such regulatory mandate, pooling all capacity in the domestic country is the optimal solution. However, the introduction of the random ban threatens the availability of the transshipment fulfillment option. As a result, it becomes advantageous to diversify and build some capacity in the overseas country if the capacity investment cost is not overly high. If this cost is high, then keeping the original strategy to pool in the domestic country is better. When the profitability of the overseas fulfillment option dominates, diversifying its capacities in the two countries remains the best option for the manufacturer. Regardless of the scenario, the manufacturer should always decrease its domestic capacity level, since it is less valuable given the potential export ban. At the same time, part of the capacity is relocated to the overseas country.

In contrast, when facing the prospect of a priority requirement, the issue of switching the capacity investment strategy from pooling to diversifying only becomes an active item for consideration when the domestic country has a larger population than the overseas country. Under such circumstances, the domestic capacity level is already relatively high when the priority requirement is absent. The likelihood of diverting capacity from the domestic country to the overseas country decreases due to the population gap. As a result, it becomes advantageous to set up capacity in the overseas country if the overseas fulfillment option is sufficiently profitable. On the other hand, when the domestic country has equal or less population than the overseas country, it is better for the manufacturer to stay with its capacity commitment strategy when there is no priority requirement and only adjust the capacity levels. In general, this means increasing the domestic capacity level, because excessive domestic capacity still can be utilized to satisfy overseas demand. However, this is not always the case. When it is optimal to diversify regardless of the priority requirement, the domestic capacity may need to be lowered, and more overseas capacity may need to be set up.

Because of the manufacturer's strategic responses to the regulatory mandates, the resulting domestic capacity investment level may not always go in the direction that aligns with the domestic government's intention. This leads to the question of how effective these regulatory mandates really are. To unpack the implications of the manufacturer's capacity investment levels on the domestic country and the global system, we evaluate how important quality outcomes change as a result of the manufacturer's capacity level adjustments. Specifically, we focus on vaccine fill rate and QALYs as the outcome measures for service level and public health, respectively. Our analysis provides mixed messages.

The good news for the domestic government is that despite the potential decrease in the domestic capacity level (especially under a random ban), the fill rate and QALYs of the domestic country do not always decrease. This is the case due to the regulatory mandates' capability of re-routing the vaccine dosages to serve the domestic citizens. The bad news, however, is that the regulatory mandates can still backfire. When the regulatory mandates result in substantial decreases in the domestic capacity level, the effect of re-routing is not large enough to compensate for capacity losses, leading to a worse fill rate and QALYs for the domestic country.

By taking these policy implications into consideration and carefully evaluating the particular scenario that the manufacturer is facing, the domestic government can be better positioned to implement a regulatory mandate that can achieve the intended goal of boosting domestic vaccine supply and public welfare. In fact, not implementing any regulatory mandate may be the optimal choice for the domestic government. For example, when the domestic fulfillment option is more profitable than the transshipment fulfillment option, choosing not to implement a mandate is the best policy. When the transshipment fulfillment option dominates the other two, a priority requirement is usually sufficient to reliably improve domestic outcomes. When the overseas fulfillment option is the most profitable and the domestic fulfillment option is the least profitable, the situation is more complex. A random ban or a priority requirement might be able to improve domestic welfare, but not implementing any mandate may be the best the domestic government can do.

A challenge that exists in reality, however, is that the domestic government may not know the relative profitability of the manufacturer's three fulfillment options. While it is plausible that the domestic government can accurately gauge how profitable the domestic fulfillment option is, the information for the other two fulfillment options may be privately known only to the manufacturer. This potential lack of complete information hampers the domestic government's ability to target a specific regulatory mandate to a specific scenario. From the manufacturer's perspective, this means that there are two ways to proactively influence the domestic government's policy. First, by sharing the information of all three fulfillment options in certain scenarios, the manufacturer can effectively prevent the domestic government's policy that will hurt its profit. Second, strategically concealing certain information in other scenarios may allow the manufacturer to avoid ending up accepting a less favorable policy. From the domestic government's perspective, correctly identifying the manufacturer's incentives and cooperating with the manufacturer may prove to be critical for maximizing the welfare of the domestic citizens. In future research, a game-theoretical framework may be appropriate to fully capture the dynamics between the manufacturer and the domestic government.

Our research also reveals the tension between the two countries. The domestic government's unilateral regulatory mandates almost always lead to worse outcomes for the overseas country in terms of vaccine fill rate and QALYs, potentially enlarging the disparities between the two countries. Another fruitful avenue for future research would be to incorporate the overseas government's actions and regulations in the analysis framework. By identifying potential deterrence strategies, actively collaborating with the manufacturer, or interfering with the cooperation between the manufacturer and the domestic government described above, the overseas government may be able to influence the domestic government's policy or the manufacturer's strategy in a way that benefits their own citizens. This research direction offers many possibilities to capture complex geopolitical risks in the global system.

Chapter 6

Conclusion

In this chapter, we highlight the managerial problems we examine in this dissertation and summarize the major theoretical contributions and practical implications.

6.1 Influence of Supplier-induced Risks on Sourcing Decisions

In recent years, firms have faced more scrutiny from various stakeholders to oversee the conduct of suppliers in their extended supply chains. Negligence of potential responsibility violations or slow response to such incidents, once uncovered by media, can result in serious business reputation and customer goodwill loss. To understand how decision-makers react to this emerging responsibility violation risk and how that differs from traditional supply disruption risk, we use analytical models and incentivized experiments to contrast buyers' sourcing decisions under the two types of supplier-induced risks from a normative and a behavioral perspective. We further expand the scope of our research to account for the potential influence of participant pools and use our risk taxonomy to help identify why buyers' sourcing decisions differ across the two risk types.

This dissertation makes the following theoretical contributions:

(1) We offer a parsimonious framework to compare two important supplier-induced risks in supply chains: supply disruption and responsibility violation risks. This comparative framework allows us to compare similarities and differences across the

two risk types so that we can develop a better understanding of what is unique for each risk type and provide tailored recommendations.

(2) We propose a risk taxonomy to systematically contrast the characteristics of decision settings of the two risk types based on structural and contextual differences. This effort not only allows us to evaluate the relative influence of each characteristic but also offers a template for future research to document the differences of other risk types.

(3) We consider the influence of cognitive and affective factors on people's decisions in our research, which differs from prior behavioral operations literature that focuses primarily on cognitive influence. This initiative reveals that cognitive processing and affective reactions influence sourcing decisions through different channels. While cognitive factors help reduce diversification and increase sole-sourcing, they do not necessarily make buyers lean toward sole-sourcing from the risk-free supplier. In contrast, affective factors improve buyers' tendency to sole-source primarily by increasing their propensity to sole-source from the risk-free supplier.

(4) We provide evidence that buyers' different ordering behaviors across the two risk types are robust for participant pools with varying management experience. The consistency of this behavior shows that decision-makers' biases and preferences are unlikely to be eliminated by management experience alone. Therefore, an intentional effort is needed to help buyers understand their decisions tendencies or nudge them toward making better decisions that can benefit multiple stakeholders.

Our studies provide a list of managerial insights for buyers and buying firms:

(1) While dual-sourcing and multi-sourcing is prevalent in practice, it is important to carefully evaluate the specific sourcing settings and not take any sourcing strategy for granted. Adopting a tailored risk management strategy to a specific risk and avoiding a blanket solution are critical. Sole-sourcing may emerge as a suitable strategy for certain settings.

(2) When the pool of potential suppliers comprises candidates with different risk and cost profiles, it is imperative for buyers to understand the risk structure clearly so

that they know how their sourcing decisions influence the overall risk exposure of their supply chains. When the scope of risk is broad and crosses over to the entire supply base, mixing-and-matching may not reduce risk level but incurs a higher cost.

(3) Sole-sourcing from and committing to a high-cost, risk-free supplier is an effective strategy. On the one hand, it avoids the detrimental effect of diversification bias. On the other hand, it is robust and fool-proof because it prevents other decision errors associated with order quantity adjustment that is necessary when sole-sourcing from a low-cost, risky supplier. Moreover, when risky events involve responsibility-related violations, it is also a 'win-win' strategy as it improves firms' profit performance and promotes social benefits.

(4) Buying firms may consider nudging buyers' decisions through training and other interventions based on the characteristics of their sourcing settings. When the scope of risk is broad, it is useful to help buyers overcome the tendency to engage in linear thinking. When the risk involves violations of business practices, subconscious priming (Welsh and Ordóñez 2014) might be helpful.

Future research on this topic may benefit from testing the implications of these results in an even broader set of risk types and measuring the effectiveness of different managerial interventions.

6.2 Influence of Regulatory Risks on Capacity Investment Decisions

Regulatory risks are emerging worldwide due to various factors, including domestic nationalism sentiments and heightened geopolitical tensions. Such risks can potentially disrupt firms' daily operations and introduce new challenges to global supply chains. Inspired by the increasing trend in national governments' active interventions to supply chains—as exemplified by vaccine export controls during the COVID-19 pandemic—we use analytical models and a numerical study to examine how regulatory mandates imposed by a domestic government can influence a vaccine manufacturer's capacity commitment strategy at domestic and overseas locations and the corresponding capacity levels.

The key theoretical contributions of this dissertation are:

(1) We introduce a way to account for emerging regulatory risks that impose export restrictions and examine how they influence vaccine manufacturers' capacity investment decisions across different locations. We take into consideration two types of regulatory mandates that exemplify a broad set of regulatory policies in practice and compare their impacts on manufacturers' capacity investment decisions.

(2) Our research provides a point of connection between the production and allocation components in vaccine supply chains (Duijzer et al. 2018) and examines how manufacturers' capacity investment decisions facing regulatory risks influence vaccine availability at different locations and result in disparities.

(3) We evaluate the consequences of vaccine manufacturers' strategic reactions to governments' regulatory mandates from multiple angles (Lemmens et al. 2016). In addition to using fill rate to assess the service level, we measure the impact on public health outcomes using quality-adjusted life year (Whitehead and Ali 2010) by taking into account the influence of herd immunity (Fine et al. 2011). This combination provides a more complete picture of the impact of governments' regulatory mandates.

It offers the following key practical takeaways:

(1) When facing the risk of governments' regulatory mandates that restrict vaccine export, vaccine manufacturers may need to consider shifting their capacity commitment strategy from pooling at one location to diversifying to multiple locations. This is especially true if the regulatory mandate in question is a random ban and the unit capacity investment cost is low. If a priority requirement is proposed by governments, the only scenario under which manufacturers need to consider switching their strategy is when exporting vaccines to the overseas market is moderately profitable.

(2) Regardless of whether manufacturers need to switch their capacity commitment strategy, the optimal capacity levels at domestic locations need to be adjusted.

Facing a random ban, manufacturers always reduce their domestic capacity levels. But facing a priority requirement, manufacturers may need to increase or decrease their domestic capacity levels.

(3) Although domestic capacity levels may decrease because of manufacturers' strategic reactions to governments' regulatory mandates, the resulting domestic service levels and public outcomes do not always deteriorate, due to the fact that the imposed mandates direct more available domestic capacities to serve the domestic market. However, if these mandates induce severe domestic capacity reductions, such policies may still backfire as domestic service levels and public health outcomes will be worse than when no mandate is imposed.

(4) Imposed regulatory mandates almost always result in worse service levels and public health outcomes at overseas locations, creating larger disparities. The overall impact of these mandates at the global system level may be negative or positive, depending on the extent to which improvement at domestic locations can compensate for loss at overseas locations.

(5) The insights generated by our research not only provide guidance for firms in the vaccine industry but also have potential values for other firms that face similar regulatory challenges in their global supply chains. On the other hand, governments may use the results from our research to evaluate the potential impact of their proposed regulatory mandates and make informed decisions.

Future research can expand the scope of this research from a behavioral angle. First, prior research in behavioral operations highlights a few interesting behavioral regularities when decision-makers approach inventory decisions with substitutability and transshipment options (e.g., Bansal and Moritz 2015, Zhao et al. 2020). Thus, it might be an important direction to investigate how decision-makers determine capacity levels across different locations facing regulatory risks so as to understand how such risks are perceived and how they influence people's decisions. Second, fairness concerns and non-financial incentives might be salient factors that influence decision-makers' choices in this context, so it will be helpful if future research can unpack the tradeoffs among these different considerations. Third, to continue our inquiry into individual differences, it may be interesting to explore what behavioral factors, such as individual nationalism, impact people's decisions in this context.

References

Bansal S, Moritz B (2015) Perceived versus actual value of product substitution flexibility: An experimental investigation. *Journal of Operations Management* 38(1):56–70.

Barton R, Ishikawa M, Quiring K, Theofilou B (2018) From me to we: The rise of the purpose-led brand, the 14th annual Accenture strategy global consumer pulse research. Technical report, Accenture.

Berinsky AJ, Huber GA, Lenz GS (2012) Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. *Political Analysis* 20(3):351–368.

Blume S (2006) Anti-vaccination movements and their interpretations. *Social Science & Medicine* 62(3):628–642.

Chae S, Mena C, Polyviou M, Rogers ZS, Wiedmer R (2019) The effects of tariff increases on supply base complexity: A conceptual framework. *Journal of Purchasing and Supply Management* 25(4):100556.

Chen L, Lee HL (2017) Sourcing under supplier responsibility risk: The effects of certification, audit, and contingency payment. *Management Science* 63(9):2795–2812.

Cho SH, Fang X, Tayur S, Xu Y (2019) Combating child labor: Incentives and information disclosure in global supply chains. *Manufacturing & Service Operations Management* 21(3):692–711.

Choi K, Narasimhan R, Kim SW (2012) Postponement strategy for international transfer of products in a global supply chain: A system dynamics examination. *Journal of Operations Management* 30(3):167–179.

Csermely T, Minner S (2015) Behavioral decisions in inventory systems with dual sourcing option: An experiment, working paper, Available at https://ssrn.com/abstract=2573565.

Dawande M, Qi A (2020) Auditing, inspections, and testing for social responsibility in supply networks Working paper, Available at https://ssrn.com/abstract=3521582.

Deo S, Corbett CJ (2009) Cournot Competition Under Yield Uncertainty: The Case of the U.S.

Influenza Vaccine Market. *Manufacturing & Service Operations Management* 11(4):563–576.

Dong E, Du H, Gardner L (2020) An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases* 20(5):533–534.

Dong L, Kouvelis P (2020) Impact of Tariffs on Global Supply Chain Network Configuration: Models, Predictions, and Future Research. *Manufacturing & Service Operations Management* 22(1):25–35.

Dong L, Kouvelis P, Su P (2010) Global Facility Network Design with Transshipment and Responsive Pricing. *Manufacturing & Service Operations Management* 12(2):278–298.

DuHadway S, Carnovale S, Kannan VR (2018) Organizational communication and individual behavior: Implications for supply chain risk management. *Journal of Supply Chain Management* 54(4):3–19.

Duijzer LE, van Jaarsveld W, Dekker R (2018) Literature review: The vaccine supply chain. *European Journal of Operational Research* 268(1):174–192.

Figner B, Weber EU (2011) Who takes risks when and why? determinants of risk taking. *Current Directions in Psychological Science* 20(4):211–216.

Fine P, Eames K, Heymann DL (2011) "Herd Immunity": A Rough Guide. *Clinical Infectious Diseases* 52(7):911–916.

Frederick S (2005) Cognitive reflection and decision making. *Journal of Economic Perspectives* 19(4):25–42.

Goldschmidt K, Kremer M, Thomas DJ, Craighead CW (2020) Strategic sourcing under severe disruption risk: Learning failures and under-diversification bias, Articles In Advance, Manufacturing & Service Operations Management, Available at https://pubsonline.informs.org/doi/10.1287/msom.2020.0907.

Guo R, Lee HL, Swinney R (2016) Responsible sourcing in supply chains. *Management Science* 62(9):2722–2744.

Gurnani H, Mehrotra A, Ray S (2012) *Supply Chain Disruptions: Theory and Practice of Managing Risk* (London: Springer).

Gurnani H, Ramachandran K, Ray S, Xia Y (2014) Ordering behavior under supply risk: An experimental investigation. *Manufacturing & Service Operations Management* 16(1):61–75.

Haidt J (2001) The emotional dog and its rational tail: a social intuitionist approach to moral judgment. *Psychological Review* 108(4):814–834.

Health F (2021) A Detailed Study of Patients with Long-Haul COVID: An Analysis of Private Healthcare Claims. Technical report, FAIR Health.

Hendriks A (2012) SoPHIE - software platform for human interaction experiments, University of Osnabrueck, working paper.

Hogarth RM, Karelaia N (2007) Heuristic and linear models of judgment: Matching rules and environments. *Psychological Review* 114(3):733–758.

Hsu VN, Zhu K (2011) Tax-Effective Supply Chain Decisions Under China's Export-Oriented Tax Policies. *Manufacturing & Service Operations Management* 13(2):163–179.

Huang L, Song JSJ, Swinney R (2017) Managing social responsibility in multitier supply chains, working paper, Available at https://ssrn.com/abstract=2837332.

Hurley L (2021) U.S. Supreme Court rules for Nestle, Cargill over slavery lawsuit. *Reuters* URL `https://www.reuters.com/business/us-supreme-court-rules-nestle-cargill-over-slavery-lawsuit-2021-06-17/`.

Johnson NF, Velásquez N, Restrepo NJ, Leahy R, Gabriel N, El Oud S, Zheng M, Manrique P, Wuchty S, Lupu Y (2020) The online competition between pro- and anti-vaccination views. *Nature* 582(7811):230–233.

Kalkanci B (2017) Supply risk mitigation via supplier diversification and improvement: An experimental evaluation, working paper, Available at https://ssrn.com/abstract=3011383.

Kelly A (2016) Nestlé admits slavery in Thailand while fighting child labour lawsuit in Ivory Coast. *The Guardian* URL `https://www.theguardian.com/sustainable-business/2016/feb/01/nestle-slavery-thailand-fighting-child-labour-lawsuit-ivory-coast`.

Knolle K, Evans D (2021) Germany passes law on tougher oversight of supply chains. *Reuters* URL `https://www.reuters.com/article/us-germany-companies-supply-chains-idUSKCN2DN1AV`.

Kouvelis P, Dong L, Boyabatli O, Li R (2011) *Handbook of Integrated Risk Management in Global Supply Chains*, volume 1 (Hoboken, NJ: John Wiley & Sons).

Kraft T, Valdés L, Zheng Y (2020) Motivating supplier social responsibility under incomplete visibility. *Manufacturing & Service Operations Management* Articles in Advance.

Kraft T, Zheng Y, Erhun F (2013) The NGO's dilemma: How to influence firms to replace a potentially hazardous substance. *Manufacturing & Service Operations Management* 15(4):649–669.

Kulkarni SS, Magazine MJ, Raturi AS (2004) Risk Pooling Advantages of Manufacturing Network Configuration. *Production and Operations Management* 13(2):186–199.

Kupferschmidt K (2020) 'Vaccine nationalism' threatens global plan to distribute COVID-19 shots fairly. *Science* URL `https://www.sciencemag.org/news/2020/07/vaccine-nationalism-threatens-global-plan-distribute-covid-19-shots-fairly`.

Lee HL, Tang CS (2018) Socially and environmentally responsible value chain innovations: New operations management research opportunities. *Management Science* 64(3):983–996.

Lee YS, Seo YW, Siemsen E (2018) Running behavioral operations experiments using Amazon's Mechanical Turk. *Production and Operations Management* 27(5):973–989.

Lemmens S, Decouttere C, Vandaele N, Bernuzzi M (2016) A review of integrated supply chain network design models: Key issues for vaccine supply chains. *Chemical Engineering Research and Design* 109:366–384.

Loewenstein GF, Weber EU, Hsee CK, Welch N (2001) Risk as feelings. *Psychological Bulletin* 127(2):267–286.

Loftus P, Hinshaw D (2020) 'Vaccine Nationalism': A New Dynamic in the Race to Quash Coronavirus. *The Wall Street Journal* URL `https://www.wsj.com/articles/geopolitical-power-play-over-coronavirus-vaccine-leaves-drugmakers-in-the-middle-11590577849`.

Lu LX, Van Mieghem JA (2009) Multimarket Facility Network Design with Offshoring Applications. *Manufacturing & Service Operations Management* 11(1):90–108.

MacDonald NE (2015) Vaccine hesitancy: Definition, scope and determinants. *Vaccine* 33(34):4161–4164.

Mahmoudzadeh M, Siemsen E (2019) Reliably responsible: Structuring supply chains for socially responsible behavior, working paper, Available at https://ssrn.com/abstract=3260168.

Menon S (2021) India coronavirus: Can all adults get vaccinated in 2021? *BBC News* URL `https://www.bbc.com/news/world-asia-india-55571793`.

Moritz BB, Hill AV, Donohue KL (2013) Individual differences in the newsvendor problem: Behavior and cognitive reflection. *Journal of Operations Management* 31(1-2):72–85.

Narayanan A, Moritz BB (2015) Decision making and cognition in multi-echelon supply chains: An experimental study. *Production and Operations Management* 24(8):1216–1234.

Palan S, Schitter C (2018) Prolific. aca subject pool for online experiments. *Journal of Behavioral and Experimental Finance* 17:22–27.

Plambeck EL, Taylor TA (2016) Supplier evasion of a buyers audit: Implications for motivating supplier social and environmental responsibility. *Manufacturing & Service Operations Management* 18(2):184–197.

Pournader M, Kach A, Talluri SS (2020) A Review of the Existing and Emerging Topics in the Supply Chain Risk Management Literature. *Decision Sciences* 51(4):867–919.

Read D, Loewenstein G (1995) Diversification bias: Explaining the discrepancy in variety seeking between combined and separated choices. *Journal of Experimental Psychology: Applied* 1(1):34–49.

Rozin P, Lowery L, Imada S, Haidt J (1999) The cad triad hypothesis: a mapping between three moral emotions (contempt, anger, disgust) and three moral codes (community, autonomy, divinity). *Journal of Personality and Social Psychology* 76(4):574–586.

Schmitt AJ, Sun SA, Snyder LV, Shen ZJM (2015) Centralization versus decentralization: Risk pooling, risk diversification, and supply chain disruptions. *Omega* 52:201–212.

Snyder LV, Atan Z, Peng P, Rong Y, Schmitt AJ, Sinsoysal B (2016) OR/MS models for supply chain disruptions: A review. *IIE Transactions* 48(2):89–109.

Snyder LV, Shen ZJM (2007) Managing disruptions to supply chains. *Frontiers of Engineering: Reports on Leading-Edge Engineering from the 2006 Symposium* (Washington, DC: The National Academies Press).

Song JS, van Houtum GJ, Van Mieghem JA (2020) Capacity and Inventory Management: Review, Trends, and Projections. *Manufacturing & Service Operations Management* 22(1):36–46.

Speier C, Whipple JM, Closs DJ, Voss MD (2011) Global supply chain design considerations: Mitigating product safety and security risks. *Journal of Operations Management* 29(7-8):721–736.

Tang S, Koval CZ, Larrick RP, Harris L (2020) The morality of organization versus organized members: Organizations are attributed more control and responsibility for negative outcomes than are equivalent members. *Journal of Personality and Social Psychology* 119(4):901–919.

Tomlin B (2006) On the value of mitigation and contingency strategies for managing supply chain disruption risks. *Management Science* 52(5):639–657.

Tversky A, Kahneman D (1974) Judgment under uncertainty: Heuristics and biases. *Science* 185(4157):1124–1131.

Tyson A, Johnson C, Funk C (2020) U.S. Public Now Divided Over Whether To Get COVID-19 Vaccine. Technical report, Pew Research Center, URL `https://www.pewresearch.org/science/2020/09/17/u-s-public-now-divided-over-whether-to-get-covid-19-vaccine/`.

Vakharia AJ, Yenipazarli A (2009) Managing supply chain disruptions. *Foundations and Trends in Technology, Information and Operations Management* 2(4):243–325.

Van Mieghem JA (2003) Commissioned Paper: Capacity Management, Investment, and Hedging: Review and Recent Developments. *Manufacturing & Service Operations Management* 5(4):269–302.

Van Mieghem JA, Rudi N (2002) Newsvendor Networks: Inventory Management and Capacity Investment with Discretionary Activities. *Manufacturing & Service Operations Management* 4(4):313–335.

Vanichkachorn G, Newcomb R, Cowl CT, Murad MH, Breeher L, Miller S, Trenary M, Neveau D, Higgins S (2021) Post–COVID-19 Syndrome (Long Haul Syndrome): Description of a Multidisciplinary Clinic at Mayo Clinic and Characteristics of the Initial Patient Cohort. *Mayo Clinic Proceedings* 96(7):1782–1791.

Vasil A (2016) Consumer watchdog calls for boycott of Nestlé candy for Halloween. *NOW* URL `https://nowtoronto.com/lifestyle/ecoholic/sumofus-nestle-halloween-candy-boycott/`.

Vela JH, Heath R (2021) Brussels blocks vaccine exports in all but name. *POLITICO* URL `https://www.politico.eu/article/vaccine-export-block-europe-coronavirus-astrazeneca/`.

Wagenaar WA, Sagaria SD (1975) Misperception of exponential growth. *Perception & Psychophysics* 18(6):416–422.

Wang Y, Gilland W, Tomlin B (2011) Regulatory Trade Risk and Supply Chain Strategy. *Production and Operations Management* 20(4):522–540.

Weber EU, Johnson EJ (2009) Mindful judgment and decision making. *Annual Review of Psychology* 60:53–85.

Weintraub R, Bitton A, Rosenberg ML (2020) The Danger of Vaccine Nationalism. *Harvard Business Review* URL `https://hbr.org/2020/05/the-danger-of-vaccine-nationalism`.

Weiss J (2021) The Biden Administration's Supply Chain Executive Order. *Industry Today* URL `https://industrytoday.com/the-biden-administrations-supply-chain-executive-order/`.

Welsh DT, Ordóñez LD (2014) Conscience without Cognition: The Effects of Subconscious Priming on Ethical Behavior. *Academy of Management Journal* 57(3):723–742.

Wetzstein A, Hartmann E, Benton Jr W, Hohenstein NO (2016) A systematic assessment of supplier selection literature–state-of-the-art and future scope. *International Journal of Production Economics* 182:304–323.

Whitehead SJ, Ali S (2010) Health outcomes in economic evaluation: The QALY and utilities. *British Medical Bulletin* 96(1):5–21.

Wilkie C (2021) Biden administration announces plans to strengthen critical supply chains. *CNBC* URL `https://www.cnbc.com/2021/06/08/biden-administration-announces-plans-to-strengthen-critical-supply-chains.html`.

Williams A, Stacey K (2021) Is there a ban on Covid vaccine exports in the US? *Financial Times* URL `https://www.ft.com/content/82fa8fb4-a867-4005-b6c2-a79969139119`.

Zhang Y, Siemsen E (2019) A meta-analysis of newsvendor experiments: revisiting the pull-to-center asymmetry. *Production and Operations Management* 28(1):140–156.

Zhao H, Xu L, Siemsen E (2020) Inventory Sharing and Demand-Side Underweighting. *Manufacturing & Service Operations Management* .

Appendix A

Appendix for Study 1

A.1 Proofs

Proof. Proof of Proposition 3.1

To begin with, we can show that $(1-\gamma_{SD})Q_L+Q_H \leqslant d \leqslant Q_L+Q_H$ in the following way:

First, we can prove that $(1-\gamma_{SD})Q'_L+Q'_H=d$ dominates $(1-\gamma_{SD})Q'_L+Q'_H>d$. If $Q'_L=0$, it is easy to see that this relationship holds. If $Q'_L>0$, for any ordering plan A (Q'_L,Q'_H) with $(1-\gamma_{SD})Q'_L+Q'_H>d$ and $Q'_L>0$, we can always construct a plan B (Q_L,Q_H) such that $(1-\gamma_{SD})Q_L+Q_H=d$, $Q_H=Q'_H$, and $Q'_L-Q_L=Q_\Delta>0$. Then we have:

$$\pi^B_{SD}-\pi^A_{SD}=(1-\gamma_{SD}\delta_{SD})c_LQ_\Delta>0.$$

Second, we can prove that $Q'_L+Q'_H=d$ dominates $Q'_L+Q'_H<d$. For any ordering plan A (Q'_L,Q'_H) with $Q'_L+Q'_H<d$, we can construct a plan B (Q_L,Q_H) such that $Q_L+Q_H=d$, $Q_H=Q'_H$, and $Q_L-Q'_L=Q_\Delta>0$. Then we have:

$$\pi^B_{SD}-\pi^A_{SD}=(1-\gamma_{SD}\delta_{SD})(p-c_L)Q_\Delta>0.$$

Since $(1-\gamma_{SD})Q_L+Q_H \leqslant d \leqslant Q_L+Q_H$, the buyer's objective function can be written as:

$$\max_{Q_L\geqslant 0,Q_H\geqslant 0}\pi_{SD}=(1-\delta_{SD})pd+[(1-\gamma_{SD})\delta_{SD}p-(1-\gamma_{SD}\delta_{SD})c_L]Q_L+(\delta_{SD}p-c_H)Q_H.$$

Because of this linear relationship, we know that we must have $(1-\gamma_{SD})Q_L^*+Q_H^* = d$ or $Q_L^* + Q_H^* = d$, and that either Q_L^* or Q_H^* must be 0.

Hence, we have the following three potential strategies to consider:

(1) $(Q_L^* = 0, Q_H^* = d)$, and $\pi_{SD}^1 = (p - c_H)d$;

(2) $(Q_L^* = d, Q_H^* = 0)$, and $\pi_{SD}^2 = (1 - \gamma_{SD}\delta_{SD})(p - c_L)d$;

(3) $(Q_L^* = d/(1 - \gamma_{SD}), Q_H^* = 0)$, and $\pi_{SD}^3 = [p - (1 - \gamma_{SD}\delta_{SD})c_L/(1 - \gamma_{SD})]d$.

It is easy to show that:

(1) is optimal if $\pi_{SD}^1 \geqslant \pi_{SD}^2$ and $\pi_{SD}^1 \geqslant \pi_{SD}^3$, i.e., if $\gamma_{SD}\delta_{SD}(p - c_L) \geqslant c_H - c_L$ and $\gamma_{SD}c_H-\gamma_{SD}\delta_{SD}c_L \geqslant c_H-c_L \Longrightarrow \frac{pc_\Delta}{c_H(p-c_L)} < \gamma_{SD} \leqslant 1$ and $\frac{c_\Delta}{\gamma_{SD}(p-c_L)} < \delta_{SD} \leqslant \frac{\gamma_{SD}c_H-c_\Delta}{\gamma_{SD}c_L}$.

(2) is optimal if $\pi_{SD}^2 \geqslant \pi_{SD}^1$ and $\pi_{SD}^2 \geqslant \pi_{SD}^3$, i.e., if $\gamma_{SD}\delta_{SD}(p - c_L) \leqslant c_H - c_L$ and $\frac{(1-\gamma_{SD}\delta_{SD})c_L}{1-\gamma_{SD}} \geqslant \delta_{SD}p \Longrightarrow (0 < \gamma_{SD} \leqslant \frac{pc_\Delta}{c_H(p-c_L)}$ and $0 < \delta_{SD} < \frac{c_L}{p-\gamma_{SD}(p-c_L)})$ OR $(\frac{pc_\Delta}{c_H(p-c_L)} < \gamma_{SD} \leqslant 1$ and $0 < \delta_{SD} < \frac{c_\Delta}{\gamma_{SD}(p-c_L)})$.

(3) is optimal if $\pi_{SD}^3 \geqslant \pi_{SD}^1$ and $\pi_{SD}^3 \geqslant \pi_{SD}^2$, i.e., if $\gamma_{SD}c_H - \gamma_{SD}\delta_{SD}c_L \leqslant c_H - c_L$ and $\frac{(1-\gamma_{SD}\delta_{SD})c_L}{1-\gamma_{SD}} \leqslant \delta_{SD}p \Longrightarrow (0 < \gamma_{SD} \leqslant \frac{pc_\Delta}{c_H(p-c_L)}$ and $\frac{c_L}{p-\gamma_{SD}(p-c_L)} < \delta_{SD} < 1)$ OR $(\frac{pc_\Delta}{c_H(p-c_L)} < \gamma_{SD} \leqslant 1$ and $\frac{\gamma_{SD}c_H-c_\Delta}{\gamma_{SD}c_L} < \delta_{SD} < 1)$.

By re-arranging the terms, we can obtain Proposition 3.1. □

Proof. Proof of Proposition 3.2

To prove Proposition 3.2, we can simply arrange the threshold conditions in Proposition 3.1 first by the impact and then by the likelihood. □

Proof. Proof of Proposition 3.3

Note that if $Q_L = 0$, the buyer's objective function is simply:

$$\max_{Q_H \geqslant 0} \pi_{RV} = p \min\{Q_H, d\} - Q_H c_H,$$

and we see immediately that $Q_H^* = d$.

If $Q_L > 0$, we can prove that $Q_H^* = 0$. For any ordering plan A (Q_L', Q_H') with $Q_H' > 0$, we can always construct a plan B (Q_L, Q_H) such that $Q_H+Q_L = Q_L'+Q_H' = Q$ and $Q_H = 0$. Then we can show plan B dominates plan A:

$$\pi_{RV}^B-\pi_{RV}^A = (Q_L'-Q_L)c_L+Q_H'c_H = (Q_L'-Q)c_L+Q_H'c_H = -Q_H'c_L+Q_H'c_H = (c_H-c_L)Q_H' > 0.$$

Hence, the objective function is simplified to be as follows:

$$\max_{Q_L>0} \pi_{RV} = (1-\delta_{RV})p\min\{Q_L, d\} + \delta_{RV}p\min\{Q_L, (1-\gamma_{RV})d\} - Q_L c_L.$$

As we see, $Q_L = d$ strictly dominates any $Q_L > d$, so we only need to consider $0 < Q_L \leqslant d$. In addition, we see that the objective function is linear with respect to Q_L no matter $0 < Q_L \leqslant (1-\gamma_{RV})d$ or $(1-\gamma_{RV})d < Q_L \leqslant d$; therefore, Q_L^* can only be d or $(1-\gamma_{RV})d$.

Hence, we have the following three potential strategies to consider:

(1) $(Q_L^* = 0, Q_H^* = d)$, and $\pi_{RV}^1 = (p - c_H)d$;

(2) $(Q_L^* = d, Q_H^* = 0)$, and $\pi_{RV}^2 = [(1-\gamma_{RV}\delta_{RV})p - c_L]d$;

(3) $(Q_L^* = (1-\gamma_{RV})d, Q_H^* = 0)$, and $\pi_{RV}^3 = (1-\gamma_{RV})(p - c_L)d$.

It is easy to show that:

(1) is optimal if $\pi_{RV}^1 \geqslant \pi_{RV}^2$ and $\pi_{RV}^1 \geqslant \pi_{RV}^3$, i.e., if $\gamma_{RV}\delta_{RV}p \geqslant c_H - c_L$ and $\gamma_{RV}(p - c_L) \geqslant c_H - c_L \Longrightarrow \delta_{RV} > \frac{c_\Delta}{\gamma_{RV}p}$ and $\gamma_{RV}(p - c_L) \geqslant c_\Delta$.

(2) is optimal if $\pi_{RV}^2 \geqslant \pi_{RV}^1$ and $\pi_{RV}^2 \geqslant \pi_{RV}^3$, i.e., if $\gamma_{RV}\delta_{RV}p \leqslant c_H - c_L$ and $c_L \leqslant p(1-\delta_{RV}) \Longrightarrow (0 < \gamma_{RV} \leqslant \frac{c_\Delta}{p-c_L}$ and $\delta_{RV} < \frac{p-c_L}{p})$ OR $(\frac{c_\Delta}{p-c_L} < \gamma_{RV} \leqslant 1$ and $\delta_{RV} < \frac{c_\Delta}{\gamma_{RV}p})$.

(3) is optimal if $\pi_{RV}^3 \geqslant \pi_{RV}^1$ and $\pi_{RV}^3 \geqslant \pi_{RV}^2$, i.e., if $\gamma_{RV}(p - c_L) \leqslant c_H - c_L$ and $c_L \geqslant p(1-\delta_{RV}) \Longrightarrow \delta_{RV}p \geqslant p - c_L$ and $\gamma_{RV}(p - c_L) \leqslant c_\Delta$.

By re-arranging the terms, we can obtain Proposition 3.3. □

Proof. Proof of Proposition 3.4

To prove Proposition 3.4, we can simply arrange the threshold conditions in Proposition 3.3 first by the impact and then by the likelihood. □

A.2 Experiment Interface Screenshots

Note: Following Gurnani et al. (2014), we balanced the sequence of the two suppliers so that the low-cost supplier is Supplier A for about half of the participants and is Supplier B for the others.

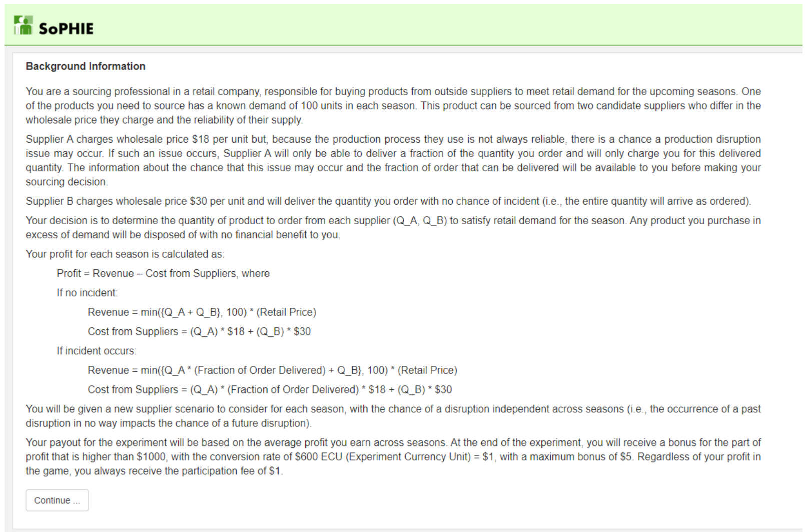


Figure A.1: Background Information of the SD Treatment

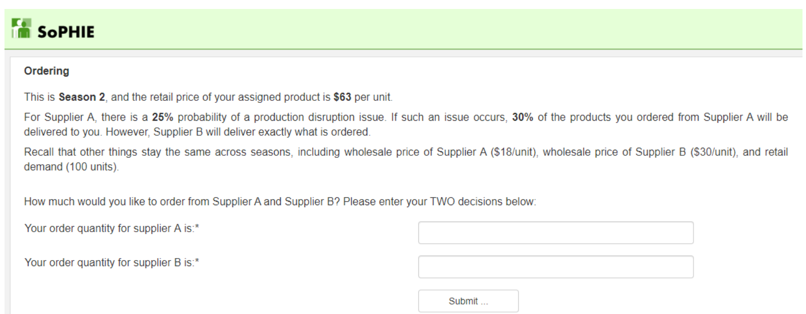


Figure A.2: Ordering Decision Page of the SD Treatment

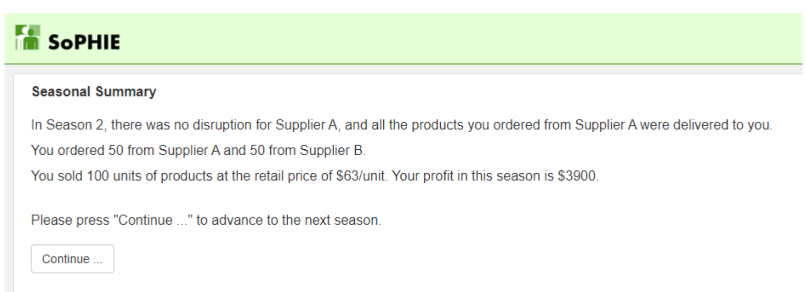
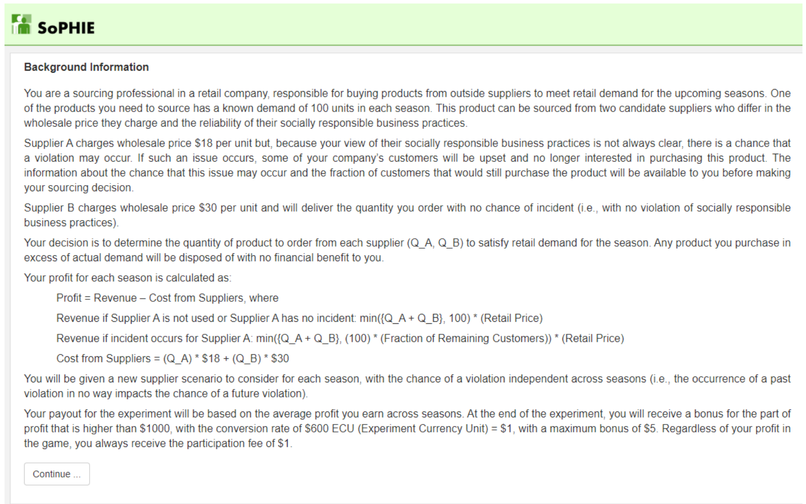


Figure A.3: Outcome Feedback Page of the SD Treatment



SoPHIE

Background Information

You are a sourcing professional in a retail company, responsible for buying products from outside suppliers to meet retail demand for the upcoming seasons. One of the products you need to source has a known demand of 100 units in each season. This product can be sourced from two candidate suppliers who differ in the wholesale price they charge and the reliability of their socially responsible business practices.

Supplier A charges wholesale price $18 per unit but, because your view of their socially responsible business practices is not always clear, there is a chance that a violation may occur. If such an issue occurs, some of your company's customers will be upset and no longer interested in purchasing this product. The information about the chance that this issue may occur and the fraction of customers that would still purchase the product will be available to you before making your sourcing decision.

Supplier B charges wholesale price $30 per unit and will deliver the quantity you order with no chance of incident (i.e., with no violation of socially responsible business practices).

Your decision is to determine the quantity of product to order from each supplier (Q_A, Q_B) to satisfy retail demand for the season. Any product you purchase in excess of actual demand will be disposed of with no financial benefit to you.

Your profit for each season is calculated as:

Profit = Revenue – Cost from Suppliers, where

Revenue if Supplier A is not used or Supplier A has no incident: min({Q_A + Q_B}, 100) * (Retail Price)

Revenue if incident occurs for Supplier A: min({Q_A + Q_B}, (100) * (Fraction of Remaining Customers)) * (Retail Price)

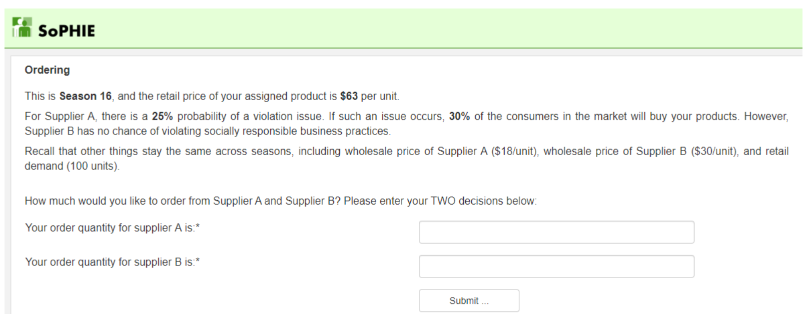
Cost from Suppliers = (Q_A) * $18 + (Q_B) * $30

You will be given a new supplier scenario to consider for each season, with the chance of a violation independent across seasons (i.e., the occurrence of a past violation in no way impacts the chance of a future violation).

Your payout for the experiment will be based on the average profit you earn across seasons. At the end of the experiment, you will receive a bonus for the part of profit that is higher than $1000, with the conversion rate of $600 ECU (Experiment Currency Unit) = $1, with a maximum bonus of $5. Regardless of your profit in the game, you always receive the participation fee of $1.

Continue ...

Figure A.4: Background Information of the RV Treatment



SoPHIE

Ordering

This is **Season 16**, and the retail price of your assigned product is **$63** per unit.

For Supplier A, there is a **25%** probability of a violation issue. If such an issue occurs, **30%** of the consumers in the market will buy your products. However, Supplier B has no chance of violating socially responsible business practices.

Recall that other things stay the same across seasons, including wholesale price of Supplier A ($18/unit), wholesale price of Supplier B ($30/unit), and retail demand (100 units).

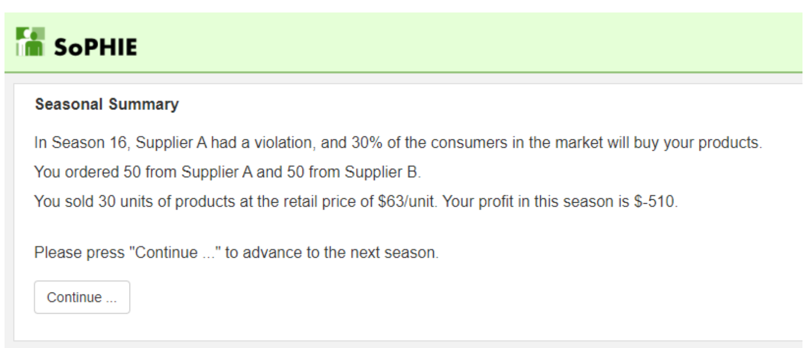
How much would you like to order from Supplier A and Supplier B? Please enter your TWO decisions below:

Your order quantity for supplier A is:*

Your order quantity for supplier B is:*

Submit ...

Figure A.5: Ordering Decision Page of the RV Treatment



SoPHIE

Seasonal Summary

In Season 16, Supplier A had a violation, and 30% of the consumers in the market will buy your products.

You ordered 50 from Supplier A and 50 from Supplier B.

You sold 30 units of products at the retail price of $63/unit. Your profit in this season is $-510.

Please press "Continue ..." to advance to the next season.

Continue ...

Figure A.6: Outcome Feedback Page of the RV Treatment

Appendix B

Appendix for Study 2

B.1 Analytical Model for the CD Treatment

We denote the likelihood of a contamination disruption by $\delta_{CD} \in (0,1)$. The impact of the disruption is captured by the parameter $\gamma_{CD} \in (0,1]$, which represents the proportion of all sourced products that would not be suitable for selling if a contamination occurs. The buyer's expected profit in this scenario is as follows:

$$\begin{aligned}\pi_{CD}(Q_L, Q_H) =& (1-\delta_{CD})p\min\{Q_L+Q_H, d\} + \delta_{CD}p\min\{(1-\gamma_{CD})(Q_L+Q_H), d\}\\ &- Q_Lc_L - Q_Hc_H.\end{aligned} \tag{B.1}$$

Proposition B.1 characterizes the buyer's profit-maximizing sourcing strategy in this setting.

Proposition B.1. *When sourcing from supplier L introduces potential contamination disruption risk, the profit-maximizing strategy is to sole-source as follows:*

(1) Select supplier H and set $Q = Q_H = d$ *when* $\gamma_{CD} > \frac{c_\Delta}{c_H}$ *and* $\delta_{CD} \geqslant \frac{c_\Delta}{\gamma_{CD}p}$;

(2) Select supplier L and

- *(a) set* $Q = Q_L = d$ *when* $\gamma_{CD} > \frac{c_\Delta}{c_H}$ *and* $\delta_{CD} < \frac{c_\Delta}{\gamma_{CD}p}$, *or* $\gamma_{CD} \leqslant \frac{c_\Delta}{c_H}$ *and* $\delta_{CD} \leqslant \frac{c_L}{p(1-\gamma_{CD})}$;
- *(b) set* $Q = Q_L = d/(1-\gamma_{CD})$, *otherwise.*

Proof. Proof of Proposition B.1.

The proof is very similar to that of Proposition 3.3 and thus omitted. □

The following proposition summarizes the insights when the likelihood level increases:

Proposition B.2. *An increase in the likelihood of contamination disruption influences the buyer's optimal sourcing strategy as follows:*

(1) Low impact condition ($\gamma_{CD} \leqslant \frac{c_\Delta}{c_H}$): the buyer always chooses supplier L but the order quantity Q_L^* increases from d to $d/(1-\gamma_{CD})$ as δ_{CD} crosses the threshold $\frac{c_L}{p(1-\gamma_{CD})}$ from below;

(2) High impact condition ($\gamma_{CD} > \frac{c_\Delta}{c_H}$): the buyer always chooses to order $Q = d$ but switches from supplier L to supplier H when δ_{CD} crosses the threshold $\frac{c_\Delta}{\gamma_{CD}p}$ from below.

Proof. Proof of Proposition B.2.

To prove Proposition B.2, we can simply arrange the threshold conditions in Proposition B.1 first by the impact and then by the likelihood.

□

B.2 Experiment Interface Screenshots: Background Information

Background Information

You are a sourcing professional in a retail company, responsible for buying products from outside suppliers to meet retail demand for an upcoming selling season. One of the products you sell has a known demand of 100 units with a retail price of $63 per unit. This product can be sourced from two candidate suppliers who differ in the wholesale price they charge and the reliability of their supply.

Supplier A charges wholesale price $18 per unit but, because their production process is not always reliable, there is a chance of a machine breakdown. If such an issue occurs, Supplier A will only be able to deliver a fraction of the quantity you order and will only charge you for that delivered quantity. You will know the likelihood of this issue occurring and its impact (i.e., the fraction of orders that will not be delivered if a machine breakdown occurs) before making your sourcing decision.

Supplier B charges wholesale price $30 per unit and has no risk of a machine breakdown.

Your decision is to determine the quantity of product to order from each supplier (Q_A, Q_B) to satisfy retail demand. Any product you purchase in excess of demand will be disposed of with no financial benefit to you.

Profit Calculation

Your profit is calculated as:

Profit = Revenue – Sourcing Cost, where

If no machine breakdown occurs at Supplier A:

Revenue = minimum of {(Q_A + Q_B), 100} * $63

Sourcing Cost = (Q_A) * $18 + (Q_B) * $30

If a machine breakdown occurs at Supplier A:

Revenue = minimum of {(Q_A) * (1 - Fraction of Order That Will Not Be Delivered) + (Q_B), 100} * $63

Sourcing Cost = (Q_A) * (1 - Fraction of Order That Will Not Be Delivered) * $18 + (Q_B) * $30

Profit Calculation Example

To help you further understand the sourcing task and profit calculations, an illustrative example is provided below:

Figure B.1: Supply Disruption (SD) Risk Treatment

Background Information

You are a sourcing professional in a retail company, responsible for buying products from outside suppliers to meet retail demand for an upcoming selling season. One of the products you sell has a known demand of 100 units with a retail price of $63 per unit. This product can be sourced from two candidate suppliers who differ in the wholesale price they charge and potential business practices they follow.

Supplier A charges wholesale price $30 per unit.

Supplier B charges wholesale price $18 per unit but, because you do not have full visibility into their operations, there is a chance that this supplier might violate labor regulations, including the use of child labor. If such an issue occurs and news of your procurement from Supplier B becomes public, a fraction of your company's customers may decide to take their business elsewhere. You will know the likelihood of this issue and its impact (i.e., the fraction of customers who will not purchase your product if such news becomes public) before making your sourcing decision.

Your decision is to determine the quantity of product to order from each supplier (Q_A, Q_B) to satisfy retail demand. Any product you purchase in excess of demand will be disposed of with no financial benefit to you.

Profit Calculation

Your profit is calculated as:

Profit = Revenue – Sourcing Cost, where

Revenue if no news of a labor violation at Supplier B becomes public: minimum of {(Q_A) + (Q_B), 100} * $63

Revenue if a labor violation occurs at Supplier B and news of your procurement from them becomes public: minimum of {(Q_A) + (Q_B), 100 * (1 - Fraction of Customers Who Will Not Purchase)} * $63

Sourcing Cost = (Q_A) * $30 + (Q_B) * $18

Profit Calculation Example

To help you further understand the sourcing task and profit calculations, an illustrative example is provided below:

Figure B.2: Responsibility Violation (RV) Risk Treatment

Background Information

You are a sourcing professional in a retail company, responsible for buying products from outside suppliers to meet retail demand for an upcoming selling season. One of the products you sell has a known demand of 100 units with a retail price of $63 per unit. This product can be sourced from two candidate suppliers who differ in the wholesale price they charge and potential business practices they follow.

Supplier A charges wholesale price $30 per unit.

Supplier B charges wholesale price $18 per unit but, because you do not have full visibility into their operations, there is a chance that the supplier might violate building safety regulations, potentially putting employees at risk. If a violation occurs and is detected during a safety audit, production would need to be shut down for a few days while the issue is addressed. In such a case, Supplier B will only be able to deliver a fraction of the quantity you order and will only charge you for that delivered quantity. You will know the likelihood of this issue occurring and its impact (i.e., the fraction of orders that will not be delivered if a building safety violation is detected) before making your sourcing decision.

Your decision is to determine the quantity of product to order from each supplier (Q_A, Q_B) to satisfy retail demand. Any product you purchase in excess of demand will be disposed of with no financial benefit to you.

Profit Calculation

Your profit is calculated as:

Profit = Revenue – Sourcing Cost, where

If no building safety violation at Supplier B is detected:

Revenue = minimum of {(Q_A + Q_B), 100} * $63

Sourcing Cost = (Q_A) * $30 + (Q_B) * $18

If a building safety violation occurs at Supplier B and is detected:

Revenue = minimum of {(Q_A) + (Q_B) * (1 - Fraction of Order That Will Not Be Delivered) , 100} * $63

Sourcing Cost = (Q_A) * $30 + (Q_B) * (1 - Fraction of Order That Will Not Be Delivered) * $18

Profit Calculation Example

To help you further understand the sourcing task and profit calculations, an illustrative example is provided below:

Figure B.3: Safety Violation (SV) Risk Treatment

Background Information

You are a sourcing professional in a retail company, responsible for buying products from outside suppliers to meet retail demand for an upcoming selling season. One of the products you sell has a known demand of 100 units with a retail price of $63 per unit. This product can be sourced from two candidate suppliers who differ in the wholesale price they charge and the scope of products they offer.

Both Supplier A and Supplier B can reliably produce the product you need at the same high quality.

Supplier A charges wholesale price $18 per unit for this product but also produces other products that are of lower quality in nature. There is a chance that a quality issue could occur with one of those other products. If such an issue occurs and news of your procurement from Supplier A becomes public, it could, by association, harm customers' perception of the product you sell. In this case, a fraction of your company's customers may decide to take their business elsewhere. You will know the likelihood of this issue occurring and its impact (i.e., the fraction of customers who will not purchase your product if such news becomes public) before making your sourcing decision.

Supplier B charges wholesale price $30 per unit and has no quality problems with other products they produce.

Your decision is to determine the quantity of product to order from each supplier (Q_A, Q_B) to satisfy retail demand. Any product you purchase in excess of demand will be disposed of with no financial benefit to you.

Profit Calculation

Your profit is calculated as:

Profit = Revenue – Sourcing Cost, where

Revenue if no news of a quality issue with one of the other products produced by Supplier A becomes public: minimum of {(Q_A) + (Q_B), 100} * $63

Revenue if one of the other products produced by Supplier A has a quality issue and news of your procurement from them becomes public: minimum of {(Q_A) + (Q_B), 100 * (1 - Fraction of Customers Who Will Not Purchase)} * $63

Sourcing Cost = (Q_A) * $18 + (Q_B) * $30

Profit Calculation Example

To help you further understand the sourcing task and profit calculations, an illustrative example is provided below:

Figure B.4: Reputation Disruption (RD) Risk Treatment

Background Information

You are a sourcing professional in a retail company, responsible for buying products from outside suppliers to meet retail demand for an upcoming selling season. One of the products you sell has a known demand of 100 units with a retail price of $63 per unit. This product can be sourced from two candidate suppliers who differ in the wholesale price they charge and the reliability of their supply.

Supplier A charges wholesale price $30 per unit.

Supplier B charges wholesale price $18 per unit but, during the shipping and handling process, there is a chance that one of the units becomes contaminated (e.g., exposed to mold or pests). If such an issue occurs, this unit may further contaminate a fraction of all units of this product in your warehouse (regardless of which supplier they were sourced from), making them unsuitable for selling to customers. You will know the likelihood of this issue occurring and its impact (i.e., the fraction of products in your warehouse that will not be suitable for selling if they become contaminated) before making your sourcing decision.

Your decision is to determine the quantity of product to order from each supplier (Q_A, Q_B) to satisfy retail demand. Any product you purchase in excess of demand will be disposed of with no financial benefit to you.

Profit Calculation

Your profit is calculated as:

Profit = Revenue – Sourcing Cost, where

Revenue if no unit from Supplier B contaminates products in your warehouse: minimum of {(Q_A + Q_B), 100} * $63

Revenue if a unit from Supplier B is contaminated and that unit further contaminates products in your warehouse: minimum of {(Q_A + Q_B) * (1 - Fraction of Products Not Suitable for Selling), 100} * $63

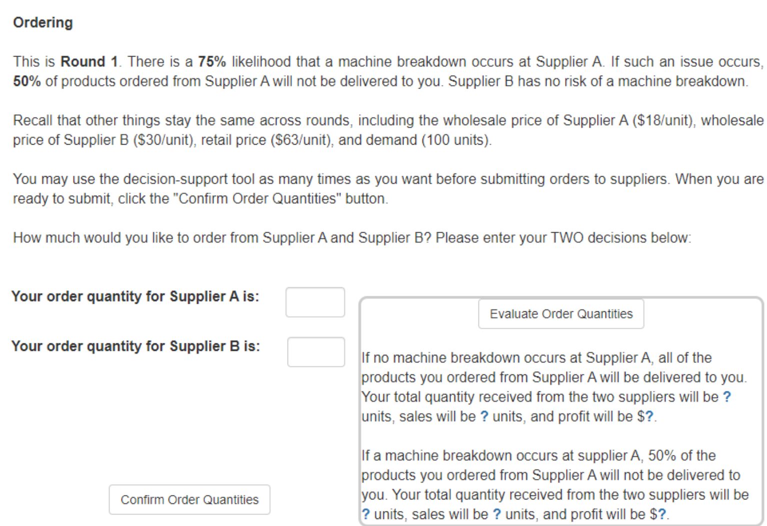
Sourcing Cost = (Q_A) * $30 + (Q_B) * $18

Profit Calculation Example

To help you further understand the sourcing task and profit calculations, an illustrative example is provided below:

Figure B.5: Contamination Disruption (CD) Risk Treatment

B.3 Experiment Interface Screenshots: Ordering Page and Outcome Feedback Page (using the SD Treatment as an example)



Ordering

This is **Round 1**. There is a **75%** likelihood that a machine breakdown occurs at Supplier A. If such an issue occurs, **50%** of products ordered from Supplier A will not be delivered to you. Supplier B has no risk of a machine breakdown.

Recall that other things stay the same across rounds, including the wholesale price of Supplier A ($18/unit), wholesale price of Supplier B ($30/unit), retail price ($63/unit), and demand (100 units).

You may use the decision-support tool as many times as you want before submitting orders to suppliers. When you are ready to submit, click the "Confirm Order Quantities" button.

How much would you like to order from Supplier A and Supplier B? Please enter your TWO decisions below:

Your order quantity for Supplier A is:

Your order quantity for Supplier B is:

Evaluate Order Quantities

If no machine breakdown occurs at Supplier A, all of the products you ordered from Supplier A will be delivered to you. Your total quantity received from the two suppliers will be **?** units, sales will be **?** units, and profit will be $**?**.

If a machine breakdown occurs at supplier A, 50% of the products you ordered from Supplier A will not be delivered to you. Your total quantity received from the two suppliers will be **?** units, sales will be **?** units, and profit will be $**?**.

Confirm Order Quantities

Figure B.6: Ordering Decision Page: Initial State

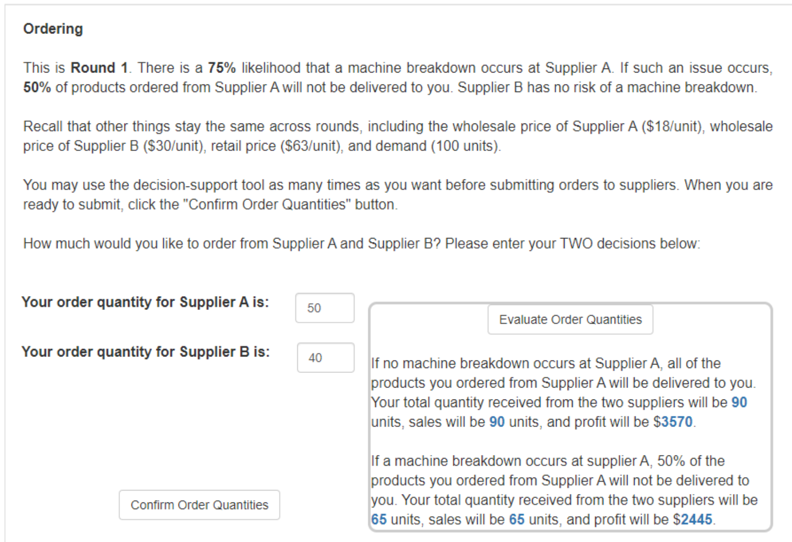


Figure B.7: Evaluating Order Quantities: Dual-sourcing

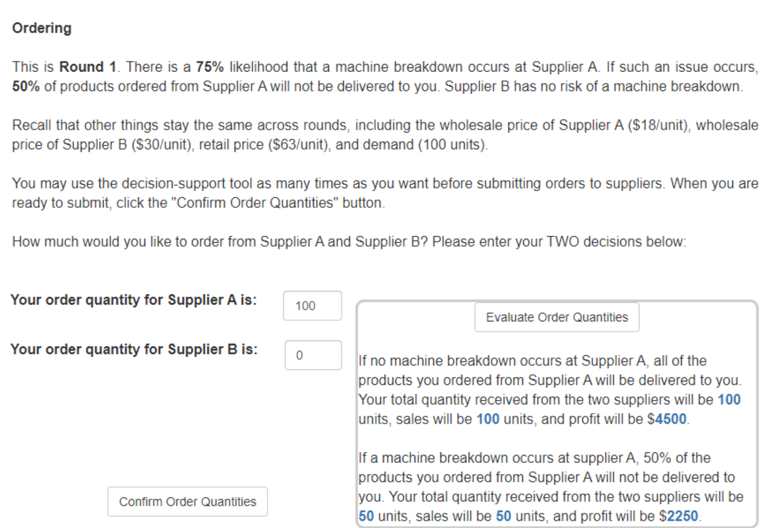


Figure B.8: Evaluating Order Quantities: Sole-sourcing from L

Ordering

This is **Round 1**. There is a **75%** likelihood that a machine breakdown occurs at Supplier A. If such an issue occurs, **50%** of products ordered from Supplier A will not be delivered to you. Supplier B has no risk of a machine breakdown.

Recall that other things stay the same across rounds, including the wholesale price of Supplier A ($18/unit), wholesale price of Supplier B ($30/unit), retail price ($63/unit), and demand (100 units).

You may use the decision-support tool as many times as you want before submitting orders to suppliers. When you are ready to submit, click the "Confirm Order Quantities" button.

How much would you like to order from Supplier A and Supplier B? Please enter your TWO decisions below:

Your order quantity for Supplier A is: 0

Your order quantity for Supplier B is: 100

Evaluate Order Quantities

All of the products you ordered will be delivered to you. Your total quantity received from the two suppliers will be **100** units, sales will be **100** units, and profit will be $**3300**.

Confirm Order Quantities

Figure B.9: Evaluating Order Quantities: Sole-sourcing from H

Round Summary

Round 1: You ordered **50** from Supplier A and **40** from Supplier B.

No machine breakdown occurred at Supplier A and so all of the products you ordered from Supplier A were delivered to you.

The total quantity received from the two suppliers is 90 units, your sales is 90 units, and your profit in this round is $3570.

Please press "Continue ..." to advance to the next round.

Continue ...

Figure B.10: Outcome Feedback: No Disruption

Round Summary

Round 2: You ordered **50** from Supplier A and **40** from Supplier B.

A machine breakdown occurred at Supplier A and so 20% of the products you ordered from Supplier A were not delivered to you.

The total quantity received from the two suppliers is 80 units, your sales is 80 units, and your profit in this round is $3120.

Please press "Continue ..." to advance to the next round.

Continue ...

Figure B.11: Outcome Feedback: Disruption

B.4 Survey Questions to Assess Linear Thinking

SD

Suppose there is a 25% likelihood that a machine breakdown occurs at Supplier A. If such an issue occurs, 70% of products ordered from Supplier A will not be delivered to you. Supplier B has no risk of a machine breakdown.

Under which scenario would there be a larger consequence if a machine breakdown occurred at Supplier A?

Scenario 1: ordering 20 units from Supplier A and 80 units from Supplier B

Scenario 2: ordering 40 units from Supplier A and 60 units from Supplier B

(i) Scenario 1

(ii) Scenario 2

(iii) Same for Scenario 1 and Scenario 2

RV

Suppose there is a 25% likelihood that a labor violation occurs at Supplier A and news of your procurement from them becomes public. If such an issue occurs, 70% consumers in the market will not purchase your product. There is no such risk with Supplier B since they always comply with labor regulations.

Under which scenario would there be a larger consequence if a labor violation occurred at Supplier A and news of your procurement from them became public?

Scenario 1: ordering 20 units from Supplier A and 80 units from Supplier B

Scenario 2: ordering 40 units from Supplier A and 60 units from Supplier B

(i) Scenario 1

(ii) Scenario 2

(iii) Same for Scenario 1 and Scenario 2

Appendix C

Appendix for Study 3

C.1 Optimal Capacity Decisions when Demand is Deterministic

When demand is deterministic instead of random, it is straightforward to obtain the manufacturer's optimal capacity investment decisions as follows.

In the base case,

$$\mathbf{K} = \begin{cases} (D_1 + D_2, 0)' & \text{if } v_O \leqslant v_T \\ (D_1, D_2)' & \text{if } v_O > v_T \end{cases}.$$

In the random ban condition,

$$\mathbf{K} = \begin{cases} (D_1 + D_2, 0)' & \text{if } v_O \leqslant (1-\delta)v_T \\ (D_1, D_2)' & \text{if } v_O > (1-\delta)v_T \end{cases}.$$

In the priority requirement condition,

$$\mathbf{K} = \begin{cases} (D_1 + D_2, 0)' & \text{if } v_O \leqslant v_T \\ (D_1, D_2)' & \text{if } v_O > v_T \end{cases}.$$

From this set of results, we can see that a priority requirement does not influence the manufacturer's optimal capacity decisions. However, a random ban may change the manufacturer's strategy. Specifically, if $(1-\delta)v_T < v_O \leqslant v_T$, the manufacturer will switch from pooling to diversifying when a random ban is imposed by the government. When v_O is either too low or too high, the random ban has no impact: if $v_O \leqslant (1-\delta)v_T$, the manufacturer always chooses to pool, while if $v_O > v_T$, the manufacturer always chooses to diversify.

C.2 Proofs

Proof. Proof of Lemma 5.1.

We start with the OT scenario (shown in Figure 5.2(1)). The shadow prices, λ, of the two capacity constraints in the second-stage problems by each region are:

Table C.1: Shadow Prices of the Two Capacity Constraints in the OT Scenario

Region	Shadow Price λ
Ω_0	$(0, 0)$
Ω_1	$(0, v_O - v_T)$
Ω_2	$(v_D, v_D + v_O - v_T)$
Ω_3	(v_T, v_O)
Ω_4	$(v_D, 0)$

Let H denote the Hessian matrix of $\Pi_{BC}(K)$. For an interior solution K^*, we have:

$$H = D_K^2 \Pi_{BC}(K) = D_K^2 \mathbb{E}\pi_{BC}(K) = D_K \mathbb{E}\lambda = \Lambda D_K P,$$

where

$$\Lambda = \begin{bmatrix} 0 & 0 & v_D & v_T & v_D \\ 0 & v_O - v_T & v_D + v_O - v_T & v_O & 0 \end{bmatrix}, \text{ and}$$

$$P = \begin{bmatrix} P(\Omega_0(K^*)) \\ P(\Omega_1(K^*)) \\ P(\Omega_2(K^*)) \\ P(\Omega_3(K^*)) \\ P(\Omega_4(K^*)) \end{bmatrix}.$$

Therefore,

$$
\begin{aligned}
H &= \Lambda D_K P \\
&= \begin{bmatrix} -v_D a_3 - v_D a_2 + (v_D - v_T)a_1 & -v_D a_2 + (v_D - v_T)a_1 \\ -v_D a_2 + (v_D - v_T)a_1 & \begin{matrix} -v_D a_2 + (v_D - v_T)a_1 - (v_O - v_T)a_4 - \\ (v_D + v_O - v_T)a_5 \end{matrix} \end{bmatrix},
\end{aligned}
$$

where

$$
\begin{aligned}
a_1 &= \int_0^\infty f(D_1, K_1 + K_2)\, dD_1, & a_2 &= \int_0^{K_1} f(D_1, K_1 + K_2 - D_1)\, dD_1, \\
a_3 &= \int_0^{K_2} f(K_1, D_2)\, dD_2, & a_4 &= \int_0^{K_1} f(D_1, K_2)\, dD_1, \\
a_5 &= \int_{K_1}^\infty f(D_1, K_2)\, dD_1.
\end{aligned}
$$

To simplify the notation, let $A_1 = v_D a_3$, $A_2 = v_D a_2 - (v_D - v_T)a_1$, and $A_3 = (v_O - v_T)a_4 + (v_D + v_O - v_T)a_5$. Then we have:

$$
H = \begin{bmatrix} -A_1 - A_2 & -A_2 \\ -A_2 & -A_2 - A_3 \end{bmatrix}.
$$

Recall that in the OT scenario, $0 < v_D < v_T < v_O$. Hence, $-(v_D - v_T) > 0$ and $v_O - v_T > 0$. As a result, $A_2 > 0$ and $A_3 > 0$. Since it is clear that $A_1 > 0$, we know that H is negative, symmetric, and diagonally dominant, guaranteeing H to be negative definite. This proves that Π_{BC} is concave in K in the OT scenario.

The proof for the other scenarios is similar and thus omitted.

□

Proof. Proof of Proposition 5.1.

(1) We start with the OT scenario (shown in Figure 5.2(1)). Suppose a boundary solution exists under which it is optimal to pool and the optimal capacity decisions are: $K^* = (K_1^* > 0, K_2^* = 0)$.

The Kuhn-Tucker conditions for optimality are:

$$\begin{bmatrix}0\\0\end{bmatrix}P(\Omega_0(K^*))+\begin{bmatrix}0\\v_O-v_T\end{bmatrix}P(\Omega_1(K^*))+\begin{bmatrix}v_D\\v_D+v_O-v_T\end{bmatrix}P(\Omega_2(K^*))$$
$$+\begin{bmatrix}v_T\\v_O\end{bmatrix}P(\Omega_3(K^*))+\begin{bmatrix}v_D\\0\end{bmatrix}P(\Omega_4(K^*))=\begin{bmatrix}c\\c\end{bmatrix}-\begin{bmatrix}\mu_1\\\mu_2\end{bmatrix},$$
$$\mu_1K_1^*=0,$$
$$\mu_2K_2^*=0,$$
$$\mu_i>0.$$

It is clear that $\mu_1=0$. Hence,

$$v_DP(\Omega_2(K^*))+v_TP(\Omega_3(K^*))=c,$$
$$v_DP(\Omega_2(K^*))-v_T\left[P(\Omega_1(K^*))+P(\Omega_2(K^*))\right]$$
$$+v_O\left[P(\Omega_1(K^*))+P(\Omega_2(K^*))+P(\Omega_3(K^*))\right]=c-\mu_2.$$

Solving for μ_2, we can get the following solution:

$$\mu_2=-(v_O-v_T)\left[P(\Omega_1(K^*))+P(\Omega_2(K^*))+P(\Omega_3(K^*))\right].$$

Recall that in the OT scenario $v_T<v_O$. Hence, $\mu_2<0$, which contradicts to $\mu_i>0$. Therefore, it is always optimal to diversify in the OT scenario. We can use the same approach to show that it is always optimal to diversify in the OD scenario.

(2) Next, we focus on the DT scenario (shown in Figure 5.2(3)). Suppose a boundary solution exists under which it is optimal to pool and the optimal capacity decisions are: $K^*=(K_1^*>0,K_2^*=0)$.

The Kuhn-Tucker conditions for optimality are:

$$\begin{bmatrix}0\\0\end{bmatrix}P(\Omega_0(K^*))+\begin{bmatrix}v_T-v_O\\0\end{bmatrix}P(\Omega_1(K^*))+\begin{bmatrix}v_T\\v_O\end{bmatrix}P(\Omega_2(K^*))$$
$$+\begin{bmatrix}v_D\\v_O\end{bmatrix}P(\Omega_3(K^*))+\begin{bmatrix}v_D\\0\end{bmatrix}P(\Omega_4(K^*))=\begin{bmatrix}c\\c\end{bmatrix}-\begin{bmatrix}\mu_1\\\mu_2\end{bmatrix},$$
$$\mu_1 K_1^*=0,$$
$$\mu_2 K_2^*=0,$$
$$\mu_i>0.$$

As $\mu_1=0$, we can solve for μ_2 and obtain the following solution:

$$\mu_2=(-v_O+v_T)P(\Omega_2(K^*))+(v_D-v_O)P(\Omega_3(K^*)).$$

Note that in the DT scenario we have $v_O<v_T<v_D$, which implies that $v_D-v_O>0$ and $v_O-v_T<0$. Hence

$$(v_D-v_O)P(\Omega_3(K^*))>(v_O-v_T)P(\Omega_2(K^*)).$$

That is to say, μ_2 is always positive. Thus, it is always optimal to pool in the DT scenario. We can use the same approach to show that it is always optimal to pool in the TM and TE scenarios.

(3) Lastly, we examine the DO scenario (shown in Figure 5.2(4)). Suppose a boundary solution exists under which it is optimal to pool and the optimal capacity decisions are: $\tilde{K}^{DO}=(\tilde{K}_1^{DO}>0,\tilde{K}_2^{DO}=0)$.

The Kuhn-Tucker conditions for optimality are:

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} P(\Omega_0(\tilde{K}^{DO})) + \begin{bmatrix} 0 \\ v_O - v_T \end{bmatrix} P(\Omega_1(\tilde{K}^{DO})) + \begin{bmatrix} v_T \\ v_O \end{bmatrix} P(\Omega_2(\tilde{K}^{DO}))$$

$$+ \begin{bmatrix} v_D \\ v_O \end{bmatrix} P(\Omega_3(\tilde{K}^{DO})) + \begin{bmatrix} v_D \\ 0 \end{bmatrix} P(\Omega_4(\tilde{K}^{DO})) = \begin{bmatrix} c \\ c \end{bmatrix} - \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix},$$

$$\mu_1 \tilde{K}_1^{DO} = 0,$$

$$\mu_2 \tilde{K}_2^{DO} = 0,$$

$$\mu_i > 0.$$

As $\mu_1 = 0$, we can solve for μ_2 and obtain the following solution:

$$\mu_2 = c + v_T P(\Omega_1(\tilde{K}^{DO})) - v_O.$$

If $c + v_T P(\Omega_1(\tilde{K}^{DO})) - v_O > 0$, or $c > v_T - v_T Pr(D_1 + D_2 \leqslant \tilde{K}_1^{DO})$, it is optimal to pool. Otherwise, it is optimal to diversify.

Rearranging the conditions based on when it is optimal to diversify vs. pool yields Proposition 5.1.

□

Proof. Proof of Lemma 5.2.

When the export ban is activated, the problem is similar to a separable two-item newsvendor problem. Since we know that a newsvendor's expected profit function is concave, we know that $\Pi_B(K_1, K_2)$ is concave. Because we have $\Pi_{RB}(K_1, K_2) = (1 - \delta)\Pi_{BC}(K_1, K_2) + \delta\Pi_B(K_1, K_2)$, and know that both $\Pi_{BC}(K_1, K_2)$ and $\Pi_B(K_1, K_2)$ are concave, we know immediately that $\Pi_{RB}(K_1, K_2)$ is concave. □

Proof. Proof of Proposition 5.2.

The proof of Proposition 5.2 is similar to that of Proposition 5.1 and thus omitted.

□

Proof. Proof of Corollary 5.1.

Corollary 5.1 directly follows Propositions 5.1 and 5.2. By reorganizing the conditions, we can show the conditions under which it is optimal to stay diversifying, stay pooling, or switch from pooling to diversifying. Corollary 5.1 selectively highlights the conditions that induce the manufacturer to change its capacity commitment strategy. The only thing that needs to be shown is that under no circumstance the manufacturer should switch from diversifying to pooling.

Suppose that under certain conditions the manufacturer may switch from diversifying to pooling. This requires: $v_T < v_O < v_D$ and $v_O - (1-\delta)v_T P_1^{DO} < c < v_O - v_T P_1$. Hence, $P_1 < (1-\delta)P_1^{DO}$. Because $0 < \delta < 1$, we know $P_1 < P_1^{DO}$, which implies

$$\tilde{K}_1^{DO} < \hat{K}_1^{DO},$$

i.e., the optimal domestic investment level in the random ban condition is greater than that in the base case. To understand the relative ordering of the two capacity investment levels, we return to the optimality conditions under the two conditions:

$$\begin{aligned} v_T(1 - P(\Omega_1(\tilde{K}^{DO}))) + (v_D - v_T)P(\Omega_3(\tilde{K}^{DO})) &= c, \\ v_T(1-\delta)(1 - P(\Omega_1(\hat{K}^{DO}))) + (v_D - v_T(1-\delta))P(\Omega_3(\hat{K}^{DO})) &= c. \end{aligned}$$

If $\tilde{K}_1^{DO} < \hat{K}_1^{DO}$, then $P(\Omega_1(\hat{K}^{DO})) > P(\Omega_1(\tilde{K}^{DO}))$ and $P(\Omega_3(\hat{K}^{DO})) < P(\Omega_3(\tilde{K}^{DO}))$. Let $x = P(\Omega_1(\hat{K}^{DO})) - P(\Omega_1(\tilde{K}^{DO}))$ and $y = P(\Omega_3(\tilde{K}^{DO})) - P(\Omega_3(\hat{K}^{DO}))$, then we have:

$$\begin{aligned} v_T(1-\delta)(1 - P(\Omega_1(\tilde{K}^{DO})) - x) + (v_D - v_T(1-\delta))(P(\Omega_3(\tilde{K}^{DO})) - y) \\ - \Big[v_T(1 - P(\Omega_1(\tilde{K}^{DO}))) + (v_D - v_T)P(\Omega_3(\tilde{K}^{DO}))\Big] = 0. \end{aligned}$$

Solving for x, we have:

$$x = -\frac{(v_D - v_T + v_T\delta)y + v_T\delta P(\Omega_2(\tilde{K}_1^{DO}))}{v_T(1-\delta)} < 0,$$

where $P(\Omega_2(\tilde{K}_1^{DO})) = 1 - P(\Omega_1(\tilde{K}_1^{DO})) - P(\Omega_3(\tilde{K}_1^{DO}))$. Note that this contradicts to $x > 0$. Hence, $\tilde{K}_1^{DO} > \hat{K}_1^{DO}$, which in turn shows that the manufacturer will never switch from diversifying to pooling.

□

C.3 Non-concavity of the Manufacturer's Expected Profit Function in the Priority Requirement Condition

In Figure C.1, we provide a counter-example to show that the manufacturer's expected profit function is not always concave in the priority requirement condition. In this example, the manufacturer's expected profit function is not concave because $(\Pi_{PR}^{TM}(3,3) + \Pi_{PR}^{TM}(55,15))/2 = 51.32 > 45.76 = \Pi_{PR}^{TM}((55+3)/2, (15+3)/2)$. The red line segment in the figure show $(3, 3, 10.34) - (55, 15, 92.30)$.

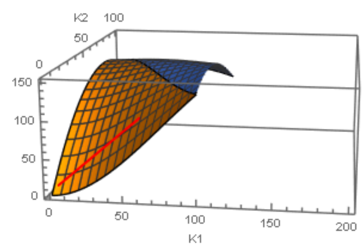


Figure C.1: $\Pi_{PR}^{TM}(K_1, K_2)$ when $d_1 = d_2 = 100$, $v_D = 1.4$, $v_O = 4.75$, $v_T = 6.14$, and $c = 1.35$